The Effect of Political Frictions on Long-term Care Insurance

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Abstract

Despite sharply rising prices, the number of companies choosing to sell private long-term care insurance (LTCI) has dropped from over 100 to just over 30 today. This paper shows that regulators' political incentives had a significant effect on both prices and insurer participation in the LTCI market. We find that four attributes of the state regulator – election cycle, political capital, political affiliation, and campaign funding – significantly affected price changes. Furthermore, companies operating in states with more political frictions earn only .48 times the profits of their counterparts and are more likely to drop out of the market. To quantify equilibrium effects of the regulator in the LTCI market, we develop and calibrate a dynamic structural model. Using counterfactual simulations, we estimate that if regulators only cared about consumer surplus and faced no political frictions, social welfare would increase by roughly $228 million per year.

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1 Introduction

Roughly 66% of Americans over age 65 are expected to need long-term care (LTC) – a service that supports individuals who struggle with Activities of Daily Living (ADLs), such as eating, showering, and dressing. The cost of these services is both high and steadily rising. For example, nursing homes, which are a popular form of LTC in the United States, have increased their average annual (nominal) costs from \$65,185 in 2004 to \$97,452 in 2017 (Genworth 2017). Despite these high costs, public financing options are limited. Medicare does not cover LTC beyond a three month period, and Medicaid only covers individuals who have little or no financial assets. Thus, private long-term care insurance (LTCI) was introduced in the 1980s to provide a financial safety net for millions of Americans (Nordman 2016). However, today, the private LTCI market is unraveling, and our paper explores a novel driver behind this market failure: regulatory frictions in product pricing.

Our paper sheds light on regulators' incentives as an important supply-side issue in the LTCI market, while the existing literature has primarily focused on demand-side issues such as adverse selection. In most studies, the role of insurance regulators are entirely ignored. However, in practice, LTCI prices are governed by the state insurance commissioner, who faces a trade-off between consumer protection and insurance company solvency. In this paper, we exploit novel data on insurance premium change applications to show that these regulators significantly limited insurers' ability to raise premiums. Overall, when regulators grant smaller premium increases, we find that insurers in their states reap lower profits and are more likely to drop out of the market.

We begin by providing evidence of mispricing in the LTCI market. For the 15 largest companies, sorted by the total value of annual premiums collected, we find that their *projected* annual costs are on average lower than the *realized* annual costs of providing LTCI. This suggests that the product was underpriced. Furthermore, between years 2009 and 2015, we find that the majority of these companies continued to underprice LTCI over time. Since both prices on new policies and price changes on existing policies must be approved by the state regulator, we hypothesize that long-run mispricing in the LTCI market may be explained by regulatory frictions. To test this hypothesis, we identify and study four political incentives facing the state regulator: election cycle, political capital, political affiliation, and campaign funding.

First, we find that premium changes are significantly smaller when the state regulator approaches election year. Moving from the year before election to the year after election implies an aggregate premium increase of 51 basis points, which is roughly 20% of the unconditional average. More precisely, using actual premium change requests submitted to the state regulator, we show that this effect is driven by insurance regulators' behavior. When the regulator approaches election time, he (1) approves a smaller number of requests, (2) approves requests with a lower probability, and (3) grants a smaller magnitude of premium increases. Since election cycles are largely uncorrelated with other pricing factors such as population demographics and consumer demand, these estimates provide some of the sharpest evidence of political frictions in the LTCI market.

Next, we look at three other political factors facing the regulator: political capital, political party, and campaign financing. We find that Democratic regulators allow smaller premium increases and are more likely to reject requests than Republican regulators. However, they are equally sensitive to the election cycle. On the other hand, regulators who were elected by a greater voting share or had a greater winning margin are significantly less sensitive to election cycles, and thus, feel less election cycle pressure. Lastly, we find that regulators with more campaign funding approve smaller price increases. This suggests that either wealthier regulators feel less pressure to help insurers in exchange for campaign donations, or regulators re-elected most often are those that emphasize consumer welfare.[1]

We conclude our empirical analysis by studying the link between regulator behavior and LTCI company dropout. Over time, profit shortfalls from political frictions can accumulate, driving insurers to exit the market. Consistent with this theory, we find that smaller premium increases are correlated with lower cash flows as well as a higher probability of company dropout across states. In addition, companies operating in the half of states with higher election-related frictions receive only .48 times the revenues of their counterparts over time. While companies in states with high frictions consistently underestimate their revenues, those in low friction states are able to adjust their pricing assumptions and generally match realized revenues over time.

Ultimately, price-setting in the LTCI market depends upon consumer demand and vice versa, so reduced-form estimates cannot capture equilibrium outcomes. Thus, we complete our analysis with a structural model of the LTCI market. In each period, the state regulator decides on a maximum allowable rate increase based upon expected company profits, expected consumer surplus, and his time until election year. Companies then decide whether to pay a fixed application cost to obtain the increase. If companies' expected profits become negative, they will drop out of the market. Using our calibrated model, we simulate counterfactual scenarios. We estimate that removing regulator election cycles and only maximizing consumer surplus in the regulator's objective function would improve social welfare by $228 million per year. Our findings suggest that a rotating committee of regulators who do not feel election pressures or need to rely on industry donations could significantly improve novel, unpredictable markets like LTCI.

The rest of our paper is organized as follows. Section 2 gives relevant background information on the LTCI market and provides evidence of persistent underpricing. We describe our data sources in Section 3. In Section 4, we show that regulators' election cycles, political capital, political affiliation and campaign financing all significantly predict the size and timing of price changes. In Section 5, we show that company profits as well as dropouts by state are correlated with regulators' strictness and sensitivity to election cycles. In Section 6, we discuss our structural model, show the calibration results, and simulate counterfactual states of the world. Finally, Section 7 concludes.

[1] Since revenues accumulate over time, incumbent regulators are often wealthier than newer candidates.

1.1 Related Literature

Our paper contributes to three existing strands of literature: failure of the private long-term care insurance (LTCI) market, political economy of financial markets, as well as applications of dynamic structural IO models.

First, we add to a rich literature exploring the causes of private LTCI market failure. One branch of this literature shows that the LTCI market is adversely selected. For example, Brown et al. (2012), Coe et al. (2015b), Ko (2016), Mommaerts (2015), and Oster et al. (2010) demonstrate that individuals who are more likely to use nursing homes are also more likely to purchase LTCI. More specifically, Hendren (2013) shows that the market has completely unraveled for the highest cost individuals. Another branch of this literature shows that demand for the product itself is low (Brown and Finkelstein (2007), Ameriks et al. (2017)). This may be either due to Medicaid crowd-out of private LTCI (Braun et al. 2018, Brown and Finkelstein 2008), the fact that people do not value bequests and thus prefer to spend down their savings (Lockwood 2014), or the consumer's ability to fund LTC using home equity (Achou (2018), Boyer et al. (2017), and Davidoff (2010)).

To our knowledge, our paper is one of only a few to focus on supply-driven causes of LTCI market failure. Comparing demand-driven to supply-driven causes of LTCI failure, Brown and Finkelstein 2007 find that there is significant evidence of supply-side inefficiencies such as imperfect competition, large transaction costs, and inability of insurers to diversify aggregate risk (see also Ameriks et al. (2016),Braun et al. (2018)). Pricing inefficiencies have largely been the focus of actuarial and regulatory reports, which find under-estimated morbidity rates and over-estimated lapse rates (Eaton 2016, Nordman 2016, Rubin et al. 2014). These studies imply that LTCI was underpriced, and if companies cannot obtain timely rate increases, growing profit shortfalls may lead to insurer dropout. To our knowledge, we are the first to test this claim systematically across the national LTCI market.

Next, this extends research on the political economy of regulators to the LTCI market, where product mispricing played a large role. Although a few studies have shown that regulators impact the insurance market (Berry-Stolzle and Born (2012), Grace and Phillips (2008)), this area remains relatively understudied. One branch of the broader political economy literature finds that public officials deliver positive news to increase popularity when they approach election year (some examples include MacRae (1977), Nordhaus (1975), and Rogoff and Sibert (1988)). In the banking sector Brown and Dinc (2005) and Liu and Ngo (2014) show that regulators delay intervention for failing banks until after election, perhaps in order to avoid unfavorable news that may influence consumers' votes. Focusing on the life insurance market, Leverty and Grace (2018) find that regulators delay bail-outs in the year prior to election. To our knowledge, our paper is the first to demonstrate political and election cycle frictions in the context of LTCI.

Finally, on the theoretical side, our paper combines and extends the contributions of two related research topics: the effect of insurance regulation on equilibrium supply and the structural estimation of infinite horizon games. Our work broadly builds upon a rich literature that models the interaction between regulation and company behavior (Lim and Yurukoglu (2018), Wolak (1994), and Abito (2014)). More specifically, in the health insurance industry, a few papers have looked at how one type of price regulation, community pricing, affects coverage rates (Simon (2005), Zuckerman and Rajan (1999)) and equilibrium outcomes (Ericson and Starc (2015), Finkelstein et al. (2009), Geruso (2017), and Clemens (2015)). However, no papers have yet looked at the role of premium changes approvals on company dropouts, and no papers have studied these models in the context of the LTCI industry. To calibrate our model, our estimation procedure utilizes methods from the infinite horizon dynamic games literature, including Ericson and Pakes (1995), Bajari et al. (2007), Pakes et al. (2007), and Pesendorfer and Schmidt-Dengler (2008).

2 Background on Long-term Care Insurance

2.1 Overview

Long-term care (LTC) is healthcare that assists with Activities of Daily Living, or ADLs, that include dressing, walking, eating, and using the bathroom. The primary receivers of LTC are the elderly, although others suffering from disabling chronic conditions, injury, and mental illness may benefit as well. Although over half of Americans over age 65 are estimated to need LTC, empirically, about 32% (19%) of healthy 60-year-old men (women) will never need to use LTC until their death (Ko 2016). This suggests that there is substantial uncertainty over whether any given individual will need LTC in their lifetime. However, the risk of being financially unprepared for LTC is high, given the large and rising costs of nursing homes, assisted living facilities, and paid home care.

In the 1980's, private LTC insurance (LTCI) was created to provide financial insurance for the high cost of LTC services, and its contracts are designed to be guaranteed renewable. This means that as long as the consumer continues to make annual premium payments, LTCI companies must honor the contract. This usually entails making daily payments to cover LTC once certain conditions are met, such as the inability to perform two or more ADLs. Premiums are set at the beginning of the contract, but they may change any time subject to demonstrated need and regulatory approval. Pricing can vary based on age, gender, very broad health conditions, as well as benefit size.

LTCI policies are difficult to price. To lock-in low premiums, the typical LTCI consumer buys the policy and starts paying annual premiums around middle-age, but he may not start collecting claims unti 20 or 30 years later. Unlike other insurance policies like life insurance, many LTCI products are uncapped, so that the final payout of the policy is uncertain at time of purchase. Finally, since the 1980s, a number of initial pricing assumptions have proven to be wrong. These include interest rate forecasts, assumed lapse rates (the rate at which customers stop paying premiums), and expected mortality rates that turned out to be too high. On the other hand, the estimated cost of healthcare was overall too low (Bodnar (2016)). These issues combined imply that LTCI premiums are underpriced.

As an insurance market, LTCI is small but economically important. Less than 10% of Americans over the age of 60 have private LTCI. As of 2014, the number of private LTCI policies in force was estimated to be 7.2 million while the total number of premiums collected was an estimated $11.5 billion. However, according to the NAIC, the maximum potential value of all in-force policies is very large due to the uncapped nature of some policy payouts: $1.98 trillion (Cohen 2016).

Today, the LTCI market suffers from both rising premiums and declining supply. Both the number of new policy holders as well as active companies in the LTCI market have steadily declined between 1995 and 2015. While roughly 100 companies were in the market in the early 2000s, only about 40 remain today. On the other hand, annual premiums have been steadily trending up over the same period. While the gross annual premium was about \$1,020 in 1995, it is a little above \$1,500 in 2015.[2]

2.2 Underpricing in the LTCI Market

Mispricing in the LTCI market appear to persist over time. As Figure 1 shows, the 15 largest companies (by premiums sold) generally underestimated costs of providing LTCI between 2009 and 2015. The expected incurred claims shown on the y-axis are estimated costs based upon each companies' pricing parameters, as approved by their regulators. If the actual costs of providing LTCI were equal to projected costs, then the points in this graph would lie on the 45-degree line. However, the majority of points lie to the right of the 45-degree line, suggesting that actual claims paid were higher than expected. In fact, following the path of these points over time, the graph further shows that companies were unable to correct their pricing assumptions in a timely manner, leading to persistant underpricing.

One significant pricing friction in LTCI is the regulation of new and existing premiums. All new premiums as well as changes to existing premiums must be reviewed and approved by the state insurance commissioner (Brewster and Gutterman (2014)). In most states, the insurance commissioner is a political position, either directly elected or appointed by the state governor to serve terms of approximately four years. Since the state commissioner has an implicit obligation to protect his constituents, which include the consumers of LTCI, he may be very reluctant to allow large premium changes. His incentives may vary depending on the political climate and timing of his election cycles. This may explain why, even within one company such as Genworth, the probability of getting a premium increase approved varies widely across states.[3]

Industry leaders have also echoed the notion that regulators have been slow to allow price increases. Genworth, one of the largest LTCI providers, has stated that "[The] Massachusetts [regulator] lags behind virtually every other state in taking timely action in response to rate increase filings and in granting necessary rate increases" (Bartlett (2017)). Furthermore, in its annual 10Q statement, Genworth makes it clear that regulatory frictions in price setting has led to its dropout from specific states, including Massachusetts: "We have suspended sales in Hawaii, Massachusetts, New Hampshire, and Vermont, and will consider similar actions [. . .] in other states where we are unable to make satisfactory rate increases..." (Genworth Financial (2018)). Supporting these claims, in a survey of 26 LTCI carriers, Gordon and Pahl (2016) find that 84% of rate increase rejections from 2013-2016 were due to political caps or non-actuarial reasons (e.g. requested increase is "unreasonable").

[2]Figure A1 plots these trends over time.

[3]Figure A2 shows plots this using data gathered between 2007 and 2017.

3 Data

Our data consists of four main components: average premiums and claims, premium change requests, election cycle timing and outcomes, and insurance commissioners' campaign contributions. Summary statistics for each of our main outcome variables as well as explanatory variables can be found in Table A3.

First, we collected annual average premiums and claims data from the National Association of Insurance Commissioner (NAIC) long-term care Experience Reports. This is a regulatory filing that all insurance companies which sold policies in the preceding year have to file. More specifically, our dataset covers all life insurance companies which filed between 1997 and 2015. Each observation corresponds to a single company, year, and state. For each observation, we observe average premiums, average claims, expected claims, and total lives in force. Expected claims were only reported in the first version of the long-term care Experience Reports, published between 1997 and 2008.

Next, historical price change requests and approval decisions come from two different data sources. First, we collect all rate histories from the California long-term care Rate and History Guide. For any company that has ever sold LTCI in California over the past ten years, this dataset contains their *nationwide* detailed rate request and decision history across the United States[4] For the remainder of companies which did not sell LTCI in California, we hand collected their rate history from pdfs uploaded to the SERFF (System for Electronic Rates and Form Filing) database. [5] An example of a PDF submission along with extracted data is shown in Figure A3. The final data spans 2007 to 2017 and contains one observation for each policy, company, state, and year.

We hand-collected political data on election cycles and voting outcomes for each state and year from 1997 to 2017 through the states' Secretary of State election results websites. For the 12 states that elect the insurance commissioner directly, we collected the winning candidate's name, political party, winning percentage, as well as winning margin. For states that appoint their insurance commissioner through their elected governor, we collected the insurance commissioner's name and political party. Lastly, Alaska, Virginia, and New Mexico appoint commissioners using a committee, and their commissioners serve without term limits, so they are dropped from our election sample.

Finally, for the 11 states that have elected commissioners and also report campaign finance information on their Secretary of State websites, we collected the total cash on hand at the beginning of the year.[6] We also recorded the total contributions received and total expenditures reported during each year.

[4]Based on our rough estimates, the California dataset covers 60% of nationwide company activity.

[5]While 35 out of 50 states currently report to the SERFF database, this is the most comprehensive database which contains LTCI companies' detailed rate history. To our knowledge, our dataset is the most comprehensive possible and should not suffer from any systematic biases.

[6]Only the state of Delaware does not report.

4 Reduced Form Pricing Results

In this section, we demonstrate that regulators' political cycles, political capital, party affiliation, and campaign financing all significantly affect premiums in the LTCI market.

We begin by examining the election cycles of insurance commissioners in Section 4.2, since it provides us with the sharpest identification of political frictions at the state level. We find that when the regulator is closer to an election, he is significantly less likely to approve a premium change request, as well as more likely to approve a lower premium change amount. On the other hand, we find that LTCI companies choose to submit premium change applications less often as well as apply for smaller rate increases when the regulator is closer to election, but this is not statistically significant.

Next, in Section 4.2.1, we examine other measures of regulators' political climate. We find that regulators are tougher, meaning that they are significantly less likely to approve a premium change request and more likely to grant a smaller rate increase, when: (1) he has more political capital, as proxied by his voting outcomes, (2) he is affiliated with the democratic party, (3) he has collected more cash-on-hand for his campaign, and (4) if he does not raise as much in campaign contributions over the same year. Interestingly, regulators with more political capital are significantly less affected by the election cycle.

Finally, as a robustness test in Section 4.2.2, we utilize the granularity of our dataset to match premium change requests on a set of detailed criterion including: company, policy characteristics, time of request, as well as size of the requested increase. This allows us to control for many unobserved characteristics that may otherwise bias our estimates. We find some evidence that election cycles matter even for matched requests across different states. More specifically, within a matched group of near-identical price increase requests, if one state regulator is closer to elections than another, then they are less likely to approve the price request.

4.1 General Research Design

To study the effect of insurance regulators on average price movements in the LTCI market, we estimate the following baseline regression:

$$outcome_{ist} = \beta_1 X_{st} + \alpha_i + \alpha_s + \alpha_t + \epsilon_{ist},$$

for company i in state s and year t.

The dependent variables, denoted by $outcome_{ist}$, largely the response of the regulator to rate change requests. They include the average change in LTCI premiums in the regulator's state, the probability that the regulator approves a request for a LTCI premium increase, and the average size of the regulator's approved LTCI premium changes. The independent variables, denoted by X_t, capture the political environment surrounding the regulator, including the timing of election cycles across states, regulators' political affiliations, regulators' political capital, and regulators' campaign contributions. α_i, α_s, α_t

represent company, state, and year fixed effects respectively. The standard errors are clustered at the state level.

4.2 Regulator Election Cycles

The LTCI market is regulated by state insurance commissioners, public officials who are either elected or (generally) appointed by the governor. In this subsection, we will examine the effect of the regulator's election process on prices in this market. We hypothesize that when the regulator or his governor is closer to election year, he becomes more hesitant to approve rate increases, because they are unpopular among his constituents and can generate negative press.[7] Subsequently, average LTCI rate increases in his state should be lower. Because the timing of election cycles are exogenous to other factors that may also drive LTCI prices, our estimates of β_1 in this section provide the sharpest estimates of the causal effect of political frictions on market pricing.

We begin by showing that election cycles had a significant effect on the average premiums consumers paid. Later, we will hone in on the mechanism by looking specifically at how regulators responded to LTCI companies' rate change requests. First, in Figure 2, for each state, we plot the number of years until election year on the x-axis and average annual change in premiums on the y-axis, residualized to state and year fixed effects. This graph shows us that as the regulator gets closer to election, the average annual change in premiums in his state becomes lower. We statistically test this relationship in Table 1, where we regress annual rate change on regulators' years-left-in-term, controlling for state and year fixed effects. We find that moving from the year before election (years left in term=1) to the year after election (years left in term=4) implies an average rate increase of 3*0.17% or 0.51%. While small in magnitude, it is economically meaningful because it is roughly one-fifth of the baseline rate change in our sample, 2.7%.

Average premiums in the market vary for many reasons other than regulator behavior, including the changing demographics of consumers. To more precisely capture the effect of the regulator on prices, in Table 2, we next focus on the component of LTCI prices that regulators directly control: premium increase requests. In the first column, we see that as regulators approach election, they approve significantly lower premium increases. We find that as the regulator moves from the year before election to year after election, he approves premium changes that are 3*0.57 or 1.71 % bigger. The economic magnitude of this is a little more than 10% of the unconditional average premium increase: 12 %.

In addition, looking at columns 2-4 of Table 2 from left to right, we find that going from the year just before to just after elections: the regulator approves 0.18 more requests; has a 5.52% higher chance of approving a new or outstanding request; and has 6.27%

[7]It is unclear whether elected or appointed regulators face less election cycle pressure when it comes to approving premium change requests, so we test this empirically in Table A1. Although appointed commissioners do not answer to voters directly, he is held accountable by the governor. In fact, because the governor has many matters which take his attention away from the insurance markets, he may be less aware of the actuarial validity of premium requests and exert more political pressure.

higher change of approving a new request. Results in the fourth column are significant at the 95% confidence level, while results in the first and third column are significant at the 99% confidence level. Taken altogether, this table shows that regulators are more stringent towards premium increase requests when they face more election pressure. This is consistent with the findings using average state-level premiums, and it supports the theory that regulators are more sensitive to premium increases around elections because they are unpopular among key voting groups.

Since LTCI companies want to maximize their likelihood of getting a premium increase approved, in Table 3, we check whether they try to time the submission of premium change requests around election cycles. To do this, they may either choose to submit premium increases right after elections or ask for bigger premium increases after elections. Indeed, we find that going from the year before election to the year just after election, companies on average ask for 0.09% bigger increases (column 1) as well as submit 0.12 more rate increase requests (column 2). However, both of these magnitudes are small and neither of these relationships are statistically significant.

While it is surprising that LTCI companies do not appear to time regulators' election cycles, there are two potential explanations. First, there is evidence that request applications are costly in time and money to put together, so it is efficient for companies to submit multiple applications at once, even to different states that have different election cycles (Nordman (2016)). Second, because premiums are designed to be constant over the life of the policy, if the company waits to send in a premium change request, they must ask for a larger magnitude increase in order to make up for lost profits. This ultimately leads to a lower probability of request approval, because there is a trade-off between the size of the rate request and the probability of it getting approved (Gordon and Pahl (2016)).[8]

4.2.1 Political Capital, Political Party, and Campaign Contributions

In addition to election cycles, there are many other ways in which political pressure could impact state regulators and insurance prices. In this section, we examine three of these factors in detail: political capital, political party affiliation, and campaign financing.

First, we hypothesize that regulators with higher political capital should feel more secure in their positions and thus face less election cycle pressure. To test this, in Table 4, we restrict the sample to only the states which directly elect their commissioners, and we regress the probability of approving a rate increase request or average size of approved increases on the regulator's election vote percentage. Vote percentage serves as a good proxy for political capital, because regulators who receive a higher share of votes are generally more popular and face less political opposition. In columns 1 and 3, we only examine the effect of election vote percentage, while in columns 2 and 4, we also interact vote percentage with the regulator's election cycle. Ultimately, we find that regulators

[8]We also find a negative correlation between size of rate request and probability of approval using our rate request data, as shown in A4.

with higher political capital are less sensitive to election cycles, as evinced by a negative and significant coefficient on the interaction term. They are also more likely to be lenient, but this result is not as consistent across specifications.

Another important measure of political capital for the regulator is winning vote margin, defined as the winner's vote percentage minus the runner-up's vote percentage. In Table 5, we next examine winning voting margins as an alternative measure of political capital. Looking at columns 2 and 4, we find that higher political capital significantly predicts higher probability of approval as well as higher average size approved. In addition, similar to Table 4, we find that regulators with higher political capital are significantly less sensitive to election cycles. On average, a one standard deviation increase in winning margin would increase approval probability by 4.5 percentage points and lower the cumulative effect of election cycles by 3.2 percentage points or 33%.

One of the platforms of the Democratic party is to provide affordable health care, using government interventions if necessary. As a result, Democratic regulators should be tougher on premium increase requests, leading to lower approval rates and lower magnitudes of rate increases. In Table 6, we examine the effect of the regulator's political party on rate request outcomes. We find that Democratic regulators are 8% less likely to grant a rate increase, and their approved rate increases are 4% lower on average. Note that while political affiliation is correlated with geography, fixed effects α_s control for unobservables at the state level. Ultimately, the economic magnitudes of these differences are large–even larger than all of the observed variation over the election cycle. However, we find that Democratic regulators face just as much election cycle pressure as regulators from other parties.

Finally, since corporations contribute financially to political campaigns, the campaign finances of the insurance commissioner may affect his behavior towards LTCI companies. To address this, we look at two dimensions of the regulator's financing: cash on hand, defined as the *stock* of wealth the regulator has at the beginning of the period, and campaign contributions, defined as the *flow* of new funding that the regulator received over the current year. Looking at columns 1-2 in Table 7, we find that wealthier regulators are significantly more stringent towards premium increase requests. This may be because they feel more secure in their positions and are less pressured to raise donations from industry. Conversely, columns 4-6 show that higher flows of campaign contributions in the same year are correlated with higher approval rates. This reinforces the hypothesis that same-year campaign contributions may come from corporations in exchange for a favor from the regulator.[9]

[9] If we interact these measures with the years-left-in-term of the regulator, we find that wealthy and non-wealthy candidates alike feel election cycle pressure. While this effect is always positive, it is not significant. We omit these results for space, but they can be shared upon request.

4.2.2 Robustness using Matched Request Design

Due to the limitations of our data, we cannot directly observe policy offerings and consumer demographics. However, they might vary across states and change systematically with election cycles. If so, they would confound the estimated effects of election cycles on regulator behavior. In this section, we utilize the granularity of our rate request data and address this concern through a matched request design.

As shown in Figure A6, we find that many companies choose to submit the same premium change request to multiple states at a time; this is efficient considering the high cost of preparing all of the actuarial evidence required when submitting a request. For example, in our sample, about 3,800 requests were submitted to two states at the same time, and 1,500 were submitted to three states at the same time. Subsequently, we match requests and assign each matched group an ID denoted α_{ijt} based on the following criterion: company, policy number, policy type (e.g. Group or Individual), policy category (e.g. Home Care Only, Comprehensive, Nursing Facility Only, Tax Qualified), time of submission, and size of requested increase. Within a matched group, we ask: do these identical requests get treated differently in different states, depending that state's election cycle schedule?

To predict regulators' decisions on the same request based on how close they are to election year, in Table 8 we estimate:

$$outcome_{ijst} = \alpha_{ijt} + \alpha_s + \text{yrs left in term}_{st} + \epsilon_{ist}$$

for each company i, matched application group j, state s, and year t.

The outcomes that we examine in Table 8 include the probability of approving a rate change request, the approved rate change, and the time until the application becomes approved. Overall, we find that requests sent to a state where the regulator is further from election year is granted a slightly bigger increase on average, is more likely to be approved, and faces a shorter delay in regulator response. However, only the results in column 2 of are statistically significant. As a result, within this matched request setting, we find evidence that election cycles significantly effect affect the probability of approval, but it does not significantly impact the size of the increase or the timing of the response.

5 Reduced Form Profit and Dropout Results

The existence of pricing frictions over extended periods of time may create significant profit losses for insurers, and as a result, increase the probability of insurer dropout. This problem may become amplified over time as widening profit shortfalls require higher premium increases, which are also harder to get approved by regulators. In this section, we examine the reduced form link between regulator stringency and insurance company dropouts, finding some evidence that both political frictions and regulator stringency can lead to lower profits and more company dropouts. These political frictions can also amplify other frictions, such as low demand and adverse selection, exacerbating the shrinkage of the market over time. Thus, in Section 6, we will expand upon these findings and account for consumer demand using a structural model.

We begin by showing the relationship between regulator stringency and company dropout. Figures 3a and 3b show that lower state stringency, proxied by a higher probability of approval and a higher magnitude of approved rate change, respectively, is correlated with less insurer dropout. In order to proxy for insurer dropout at the state level, we count a firm as dropped in a state if they have not filed a LTCI experience form with the NAIC for that state in that year. This is a conservative and potentially delayed measure, because companies are required to file as long as they have sold LTCI in the previous year.[10] To address these concerns, we conduct a robustness test using nationwide data in Section 5.1.

Next, in Figure 4, we focus on the mechanism behind insurer dropouts by examining cumulative company profits over time. More specifically, we study two political factors of the regulator that may suppress prices and reduce profits, as shown earlier in Section 4.2. First, in Panel A, we compare companies in states with high election cycle frictions to those with low election cycle frictions. Election cycle friction is calculated by regressing the probability of approving a premium change request on election cycles for each state. High friction states are then defined as the half of states with the highest estimated coefficient on election cycles, β_1. Second, in Panel B, we compare companies in states with Democratic regulators, who are much more stringent towards premium increase requests, to those in states with Republican regulators.

Profits are difficult to measure using cash flows, since they are sensitive to the age of the policy and the demographics of policyholders, which vary across states. To get the most holistic view of profits, we look at two different measures of profit. The first measure, shown on the left of Panels A and B, is total cumulative revenue, which is simply calculated as total premiums collected minus total claims paid out. The second measure, shown on the right, measures the gap between actual and expected revenue, based on the companies' reported pricing assumptions. While the second measure is noisier, it controls for attributes of the policy-holder and policy age, since they are key pricing parameters.

[10] More specifically, even if a company has dropped out of a state, they may still file a form because they continue to service existing customers. In this way, this measure of dropout is correlated with actual dropout but is noisy.

In Panel A of Figure 4, we see that companies operating in states with high election cycle frictions consistently earned less profits than those operating in states with low election cycle frictions. The magnitude is economically large; over roughly 15 years, companies in high friction states earned rougly $6 billion USD less in total cumulative cash flows. To put this number in perspective, the profits earned in high friction states are only .48 times that of low friction states. Looking at the right-hand graph, we see that this can be explained by their respective pricing assumptions. More specifically, companies experiencing low frictions was able to roughly match expected to actual revenues over time. On the other hand, companies experiencing high frictions under-estimated revenues by about $800 USD per customer over time. Overall, these findings suggest that election cycle frictions may amplify over time; they have significantly negative effects on both companies' profits and, ultimately, companies' decisions to sell LTCI.

In Panel B of Figure 4, we see that companies operating in stringent states, as proxied by having a Democratic regulator, consistently earned less profits than those operating in states with Republican regulators. The magnitude is slightly smaller than that of Panel A but is also economically large. Over the 15 years in this sample, companies with Democratic regulators earned rougly $4 billion USD less in total cumulative cash flows. In addition, companies with Democratic regulators under-estimated revenues by about $400 USD per customer more than companies with Republican regulators over time. While party affiliation is only one determinant of regulator stringency, these findings suggest that they are a large determinant of company profits, and as a result, company dropouts.

5.1 Robustness Test of Dropout Data

In this section, we conduct a robustness test of dropout results using national data. While we could only infer dropouts at the state level, the NAIC actually reports dropout data at the national level. In particular, for each company and year, the number of new versus existing policies sold are reported separately; as a result, we know that a company has dropped out of the market if it has not sold any new policies. Because it is neither constructed nor inferred, this measure of company dropout is more reliable than those used in Figures 3a and 3b.

In order to estimate the effect of state-level regulator stringency on national-level dropout, we utilize variation in companies' geographic concentrations. As shown in Figure A5, LTCI companies concentrate in very different geographies. For example, Bankers Fidelity is largely concentrated in the southeast and Texas, while Unum is more dispersed, with its highest concentration in the West Coast and the Midwest. This geographic variation allows us to run regressions at the company level, where each company is "treated" by their market concentration in each state multiplied by either the regulatory stringency (as measured by average approval rate) or the average sensitivity of that state's regulator to election cycles.

We summarize our results in Table 9. In column 1, supportive of our findings in Figure 4, we see that companies are significantly more likely to drop out if they are exposed to more election cycle frictions. In column 2, we see that companies are more likely to drop if they are exposed to states that have received more premium increase requests, as well as those that grant smaller rate increases. This is consistent with our state-level findings that states with tougher regulators experience lower profits and higher dropouts. In column 3, we find that companies are more likely to drop out if they receive less revenue, as measured by higher earned premiums and lower paid claims. Finally, in column 4, we add all of the explanatory variables at once. We find that the strongest explanatory variables include: applications received, rate increase approved, as well as total earned premiums.

6 Structural Model

In order to quantify the equilibrium effect of regulatory frictions on the LTCI market, we combine insurers' supply and consumers' demand using a structural model. More specifically, we build an infinite-horizon dynamic game between a regulator and LTCI company j, in which they negotiate the future price of LTCI. For tractability, we model one representative insurance policy. Each period is one year, and the players are forward-looking but discount future payoffs with factor β.

The state space consists of the insurer's annual premiums per person p, annual costs per person t, and the years left until the election year y. The cost of providing LTCI includes a base amount as well as a per-period random shock, θ. This is observed by both the regulator and insurer, but it is unknown in advance. θ is a crucial parameter in our model, because it captures uncertainty in healthcare costs as well as mispricing of key parameters, such as lapse rates. The interaction of large cost shocks with regulatory incentives create the key market friction in our model.

In each period, the regulator weighs expected future consumer surplus against insurer profits, and the weights depend upon his position in the election cycle. This is a reduced-form strategy to model the insurer's incentives, and it is equivalent to the regulator choosing between consumer votes and industry donations, which vary in importance across his political cycle. Based upon these considerations, the regulator chooses a maximum allowable per-person premium increase, $\hat{p}$. After observing $\hat{p}$, the insurer chooses whether to spend a fixed application cost to obtain the rate increase. If the company expects to make zero or negative profits over all future periods, then it will drop out of the market.

Ultimately, we focus on pricing inefficiencies in this paper, modeling only one insurer and abstracting away from market structure considerations. As we will demonstrate, the empirical and calibrated substitution elasticities in this market are small, so the behavior of a single firm in this market effectively has no effect upon its competitors. In addition, there are always over 100 firms in the LTCI market, each with small market shares. In essence, we assume that each insurer is perfectly competitive.

6.1 Model: Consumer Demand

There are a finite number of consumers, N, in the LTCI market. For tractability, we assume that each consumer has logit demand preferences over the J LTCI insurers in his state. That is, in each period, consumer i's utility from insurer j is

$$U_{ij} = \beta_j - \alpha p_j + \epsilon_{ij}$$

where ϵ_{ij} is i.i.d and follows an extreme value distribution with mean 0, β_j is an unobserved company fixed effect, and p_j is the price of company j's LTCI policy.

In addition to choosing between the J insurers, consumers can also choose the outside option, which is to buy no insurance (j=0) at price 0. In our model, the consumers do not have any expectations over future price changes, so the consumer's problem is not dynamic. In each period, the consumer either chooses to continue paying premiums and remain covered by the policy, or switch to another policy, including the outside option.[11] It follows that the market share s_j of company j is

$$\ln s_j = \beta_j - \alpha p_j + \ln s_0 - c \tag{1}$$

where s_0 is the percentage of participants in the market who choose to buy no insurance and c is the average utility of these participants. We estimate α_j, β_j using instrumental variables, because p_j could be endogenously correlated with s_j.

Finally, following from consumer demand, expected consumer surplus is the discounted sum of average consumer surplus for company j from all future periods.

$$E[CV(p_j, \omega; \nu)] = \sum_{m=0}^{\infty} \beta^m E[(\beta_j - \alpha p_{jm}) * N_{jm} | p_{j0} = p_j; \beta_j, \alpha].$$

For tractability, we only follow one representative cohort of consumers in our model. Thus, if the insurer chooses to drop out, consumer surplus will become 0. In this way, there are welfare consequences of insurer dropout, but they do not account for future customers who may lose the option value of purchasing from insurer j.[12]

6.2 Model: Insurer Problem

On the supply side of the model, the per-period insurer payoff, $u_j(apply_j, drop_j)$, is equal to per-period profits. As long as a company has not dropped out of the market, profits are a function of the total customers, $N = s_j * Q$, unit price p_j, unit cost t_j, regulator years-left-in-term y, application cost $AppCost$, maximum allowable rate increase $\hat{p_j}$, and current period cost shock θ_j:

$$\begin{aligned} u_j(apply_j, drop_j) = (p_j * (1 + \hat{p_j} * \mathbb{1}(apply_j = 1)) - t_j * (1 + \theta_j)) * N \\ - AppCost * \mathbb{1}(apply_j = 1) + ScrapValue \end{aligned} \tag{2}$$

$ScrapValue$ captures the inherent value of the insurance business line, including earned interest income and cost of equity capital Nissim (2010). It also includes the value of simply staying in business, since LTCI companies may not costlessly exit and re-enter the market. To sell LTCI, companies must have up-to-date licenses, actuarial models, sales staff, and most importantly, consumer trust (Eaton (2016), Cummins and Danzon (1997), Cohen et al. (2013)).

[11] Theoretically, this specification suggests that consumers can costlessly switch between policies. This is not always true because switching policies forfeits past premium payments to the existing insurer and potentially creates higher premiums. We address this by estimating demand elasticities from the data, and incorporating the very small effect of changing prices upon consumer demand.

[12] Without considering future consumers, regulators underweight the effect of company dropout on consumer surplus in our model. We can address this in future work by introducing market structure dynamics that take into account decreasing competitiveness as a result of company dropout.

The insurer's dynamic problem is to choose application $apply_j$ and dropout $drop_j$ in each period to maximize:

$$V_j(p_j, t_j, y; \mu) = \max\{0, u_j + \beta E[V(p'_j, t'_j, y'; \mu)|p_j, t_j, y, \omega]\} \tag{3}$$

where p' is next period's premium level and t' is next period's claims. If the maximum is the first term on the right-hand side of Equation (3), then the insurer drops out of the market. Profits are subsequently zero in all future periods.

6.3 Model: Regulator Problem

As long as the insurer j chooses to stay in the market, in each period, the regulator chooses an allowed rate increase $\hat{p}$ to maximize:

$$V_r(p, t, y; \omega, \nu) = \underbrace{E[CV(p, \omega; \nu)]^{0.5} * E[V_j(p, t, y; \omega, \nu)]^{0.5}}_{\text{geometric mean of consumer surplus and profits}} + \underbrace{\gamma * CV(p, \omega; \nu)/y^{\kappa}}_{\text{election pressure}} \tag{4}$$

where γ and κ are parameters to be estimated.

When choosing $\hat{p}$, the regulator considers both future expected insurance profits V_j as well as consumer surplus CV_j. In the context of political incentives, these terms capture considerations for industry campaign donations and constituent votes respectively. The regulator may raise donations throughout his election cycle, but as election year approaches, it is strategic for him to focus more on gathering constituent votes. This intuition is supported by our empirical findings as well as past literature on the incentives of regulators (for example, see Canes-Wrone et al. (2001) and Maskin and Tirole (2004)). We use a reduced-form approach to capture this election cycle trade-off by adding a term that puts more weight on CV_j as election year approaches.

In the first term of Equation (4), the regulator places equal weight on consumer surplus and insurer profit. While the mission statement of most commissioner offices is to protect the consumer, many regulators maintain social and professional ties with industry leaders. In fact, after their tenure as regulator, commissioners may become industry consultants or take positions on insurance company boards. Thus, it is reasonable for insurance regulators to care about insurer profits. In this paper, we take a neutral stance and assume that outside of election considerations, consumer and insurer surplus are equally important to regulators. This is equivalent to assuming that regulators maximize total social surplus.

In the second term of Equation (4), regulators place more weight on CV_j as years-left-in-term, y, decreases. This term captures the intuition that regulators become more sensitive to the wishes of their electorate as they approach election time. γ can be interpreted as the overall level of importance regulators assign to the election cycle, and κ represents how much election cycle pressure the regulator faces across the election cycle. We allow κ to potentially be non-linear, because Leverty and Grace (2018) find that regulatory behavior becomes significantly more sensitive to election pressure in the year before an election.

If the true consumer surplus weight is higher than 0.5, our estimate of γ, the overall level of importance regulators assign to the election cycle, and $AppCost$ from equation 3 will be overestimated. $ScrapValue$ will be underestimated. However, the optimal price and dropout policies, as well as the relative welfare effects of each counterfactual scenario should remain unbiased. This is because the positive price effect of a higher consumer weight on consumer welfare will be offset by the lower γ.

6.4 Equilibrium Definition

We define a strategy profile to be a markov perfect equilibrium (MPE) if:

- The insurer's policies are optimal given its value function and the regulator's policy functions.
- The regulator's policy functions are optimal given its value function and the insurer's policy functions.
- The insurer's value function and regulator's value function are equal to the expected discounted sums of per-period payoffs implied by the policy functions of the regulator and insurer.

6.5 Discussion of the Game

The players' incentives are as follows. Insurers always want to raise prices, since it strictly increases profits if consumers do not drop their policies. On the other hand, consumer welfare is strictly decreasing in prices as long as the insurer does not drop out. The regulator cares about both insurer profits and consumer welfare. Thus, if costs are higher than expected, then the regulator has an incentive to raise prices but also keep prices from being too high.

Even if a rate increase is necessary to maintain non-negative profits in the current period, it may not be approved if the increase is large in magnitude. If an insurer does not obtain the requested rate increase in the current period, any revenue shortfalls will persist into subsequent years as well. Furthermore, if costs are rising every year, then companies will require even higher future premium increases to maintain non-zero profits. The accumulation of revenue shortfalls over extended periods of time lowers the present discounted value of insurer profits and increases the probability of insurer dropout.

The regulator values consumer welfare more and is tougher on premium increases as he approaches election year. When rate increases are needed, companies have to decide whether they will accept a lower rate increase immediately or to delay. As profit shortfalls accumulate over time, the required premium increase is greater in subsequent years when the insurer chooses to delay. If the required increase is too high, the regulator may not grant it even in the year after election. Therefore, frictions caused by election cycles overall lower insurer profits and exacerbate cumulative losses over time.

6.6 Model Estimation

6.6.1 Model Inputs

Data for insurer profits (eg annual premiums, annual claims, and number of lives covered), election cycles, and company dropouts are discussed in detail in Section 3.

The total size of the LTCI market, N, is taken from the US census. It is calculated as the number of individuals aged 50 and over who do not have Medicaid in each year and state, and it is estimated to be about 1.18 million customers based upon our data. Company market shares are calculated by dividing lives covered by each company by the total market size in each state and year.

We drop all observations that have any negative or missing values for the variables listed above. Our final estimation sample has 2,803 company-state-year observations for model estimation, spanning the years 2009-2015. A table summarizing the descriptive statistics of all variables in our estimation sample is shown in Table A4.

6.6.2 Calibration of Demand Elasticity

From Equation 1, estimates of α and β_j will be used to calculate consumer surplus. We estimate these parameters using the following equation:

$$log(s_{sjm}) - log(s_{s0m}) = c + \alpha p_{sjm} + \beta_j + \delta_s + \rho_m + \phi_{sjm} \tag{5}$$

for state s, company j, and year m. The estimating equation includes state, year, and company fixed effects.

Ideally, we would examine the decisions of old and new customers separately, because the demand functions of old and new customers are different. Older customers tend to be more liquidity constrained and price sensitive, but they are also locked into a revolving contract so their costs of switching policies are higher. Since we only observe aggregate prices and aggregate demand for each company, we instead estimate the demand for an average representative consumer.

In our model, the LTCI company cannot discriminate between old and new policies. If price discrimination actually plays a significant role in the market, then our company profits may be underestimated and our model fit may be worse than the case with price discrimination. However, in order to maintain fairness between old and new consumers, regulatory pressures may keep the presence of price discrimination quite low in practice.[13]

Since market prices and market share jointly influence each other, we use state insurance commissioner election cycles as an instrumental variable for company premiums. As demonstrated in earlier sections, election cycles significantly affect insurance prices. However, the prices of LTCI policies do not affect state election cycles, making this a good candidate for a price instrument. Using the instrumental variable model, we estimate a value of 0.00046 for α.

In addition to estimating consumer surplus in each period, our estimate of α is used to understand how market share s_j for company j changes as p_j changes. Because empirical α is small, it suggests that the effect of competitor companies' prices has a small effect on own company demand. To calculate these demand elasticities, we use the established relationship between market share and price in logit demand models:

$$\frac{\partial s_j}{\partial p_j} = -\alpha * s_j * (1 - s_j)$$

$$\frac{\partial s_j}{\partial p_k} = \alpha * s_j * s_k$$

6.6.3 Calibration of Other Parameters

Estimation parameters β_j and s_j are set to represent a typical company across all states and years. For our baseline calibration, we use the average of all company fixed effects from the estimation of equation 5 as an estimate for β_j. We use the average 0.275% (representing roughly 3,245 customers) as the starting market share of company j. We use a vector of length 29, with elements ranging from 0.00264% to 3.1308% for the market shares of company j's competitors in the market. The market size N is the average number of individuals aged 50 and over who do not have Medicaid across each year and state.

Each period, the annual per-person cost shock a company faces is drawn from a normal distribution with mean \$352 and standard deviation \$1,354, the average and spread of the difference in expected and actual claims per person found in our sample. We fix the yearly discount factor of the players, β, at 0.86 (Lim and Yurukoglu (2018)).

[13]It is reassuring to note that when we spoke to state regulators, they stated that they do not condone price discrimination between old and new policyholders. For example, they would not allow higher prices on new policyholders in order to offset losses on existing policyholders.

6.7 Estimation Steps

6.7.1 Overview

We estimate four parameters: the cost of applying for a price increase $AppCost$, the inherent value of the LTCI business line $ScrapValue$, and parameters γ and κ that govern regulator stringency.

To solve for $\mu = (AppCost, \gamma, \kappa, ScrapValue)$, we use a two-step procedure for dynamic games following Lim and Yurukoglu (2018). This method was first developed by Hotz and Miller (1993a) and Hotz et al. (1994), and then further refined by Bajari et al. (2007), Pakes et al. (2007), and Pesendorfer and Schmidt-Dengler (2008). This procedure avoids a computationally costly re-solving of the full dynamic model to obtain optimal value and policy functions. Instead, in the first stage, empirical policy functions are estimated non-parametrically, and these estimates are used to forward-simulate value functions. At each point in the state space, these value functions are used as continuation value function estimates to calculate optimal policy choices. Finally, we estimate the structural parameters by choosing the parameters that generate policy choices most closely matching key data moments.

6.7.2 Detailed Description

More specifically, the estimation procedure is as follows. We discretize the state space into a three-dimensional matrix of 20 points for the price level, 20 points for the cost level, and 4 points representing each year of a regulator's term. Given a set of candidate parameters and a position in the state space, we obtain empirical estimates of regulator and insurer decision rules (also known as empirical policy functions). To do this, we run a linear regression of each decision on our three state variables: premiums, costs, and years-left-in-term. The decision rules we estimate include company rate increase application, size of requested price increase, as well as insurer dropout.

Starting from each point in the state space, we forward-simulate insurer and regulator actions for 100 periods including random normal cost shocks, and we average the discounted sum of flow payoffs over all simulated paths to derive the continuation value. The optimal policies chosen are the actions that maximize player utility, given the estimated continuation values.

To calculate how company j market share changes if company j applies for a rate increase, we use successive competitor best-replies that maximize their profit functions. In particular, we set optimal competitor h prices at $\frac{1}{1-s_h} + cost_h$. This equation comes from maximizing truncated regulator utility $= (price_h - cost_h)^{0.5} * N_h$, where $N_h = Q * \frac{ds_h}{dp_h}$. Here, we conservatively assume that regulators do not care about consumer surplus and estimate an upper bound on the effect of competition in the market. In general, prices approach convergence after one or two iterations of competitor best replies, suggesting that there are only small effects on competitors when an insurer updates pricing.

To evaluate model fit, our criterion function compares the estimated optimal policies to the true observed policies in the data. Following Lim and Yurukoglu (2018), we minimize the squared difference between observed policies and predicted policies averaged over different points in the state space. In other words, we match the following moments:

$$M(\mu) = \begin{bmatrix} \frac{1}{N_{p,t,y}} \sum_{p,t,y} \left(\hat{p}(p,t,y) - \hat{\hat{p}}(p,t,y;\mu)\right) \\ \frac{1}{N_{p,t,y}} \sum_{p,t,y} \left(apply(p,t,y) - \widehat{apply}(p,t,y;\mu)\right) \\ \frac{1}{N_{p,t,y}} \sum_{p,t,y} \left(drop(p,t,y) - \widehat{drop}(p,t,y;\mu)\right) \\ \frac{1}{N} \sum_{i=1}^{N} \hat{p}_i - \bar{\hat{p}}_i(\mu) \\ \frac{1}{N} \sum_{i=1}^{N} apply_i - \overline{apply_i}(\mu) \\ \frac{1}{N} \sum_{i=1}^{N} drop_i - \overline{drop_i}(\mu) \end{bmatrix} \tag{6}$$

where $\hat{x}$ for policy x denotes the optimal choice at point (p, t, y) in the state space implied by μ. N denotes the number of observations in our data sample, and $N_{p,t,y}$ denotes the number of observations at point (p, t, y) in the state space. We minimize the weighted sum of squares $\hat{\mu} = \underset{\mu}{\operatorname{argmin}}(M(\mu)'WM(\mu))$, where W is the identity matrix. We compute confidence intervals using a bootstrap procedure.

6.8 Estimation Results

We present some heuristic arguments for the identification of our structural parameters. The cost for an insurer to apply for a rate increase is identified by variation in application rates across the state space. As application rates rise, the estimated cost of application falls. Insurer scrap value is identified using empirical dropout rates. As observed dropout rates rise, the estimated scrap value falls. Finally, the variation in average rate increases help identify the election pressure parameters. As average price increases rise, estimated γ rises. As price increases in states with regulators that are just elected become higher relative to price increases in other states, κ rises. In other words, differential price increases throughout the election cycle help identify κ separately from γ.

Table 10 shows the parameter estimates from our model. On average, the cost of applying for a rate increase is around \$100 per application. This estimate is small but nonzero, which is reasonable because insurers have to calculate actuarial costs and fill out the appropriate forms. The value of the LTC business ($ScrapValue$) is around \$4.7 million, roughly 67.5% of average annual premiums and 182% of average annual profits, per company, state, and year. The positive estimates of κ and γ. are consistent with the perception that insurance commissioners face significant election pressure, and that this pressure increases as election year approaches.

6.8.1 Model Predictions

In Figure 5, we plot the optimal policy functions from our calibrated model as a function of the regulator's years-left-in-term. Overall, we see that approved premium increases and application rates decrease across the election cycle. As election considerations become more salient, regulators increase their weight on consumer surplus and decrease approved price increases. This lowers the likelihood that insurers will apply for rate increases as an election draws near and increases the likelihood they will need higher rate increases in the future. The net present value of future profits also decreases.

In Figure 6, we plot the optimal policy surfaces at the estimated parameters as functions of profit-per-capita and regulator's years-left-in-term. As illustrated, application rates and approved rate increases decrease as an election year approaches. Both policies also increase as profits decrease. When profits are positive and large, regulators do not approve any rate increases, and companies cannot apply for one. Conversely, when profits are very negative, companies will apply for rate increases even if they are very small. Finally, optimal dropout policy behaves in the opposite way. When profits are very negative, companies drop out of the market because they cannot obtain the high rate increases they need for non-zero profits.

6.8.2 Model Fit

The model fit based on these moments are represented in Table 11 and Figure 7. In general, the targeted and simulated moments in Table 11 match well.

In Figure 7, we show the conditional moments across the election cycle, which are untargeted by the model but arises from the election cycle term in Equation (4). We see that our model produces downward sloping patterns in price increases and application rates as election time nears, which fits with our empirical findings. Also, our model is able to capture the relatively high rates of price increases and application rates seen in the data.

One notable deviation is that premium increases are higher in the model than empirically observed. For simplicity, our model assumes that insurers apply for a price increase already knowing what they receive. Thus, insurers would never apply to receive a price increase of 0%, and regulators never reject a request. In contrast, in the data, we find that many rate increase applications are rejected, and rate increases of 0% are often observed. As a result, the prices and application rates in our model appear more sensitive to elections than the empirical data.

Finally, our model also predicts a small increase in dropout rates as the regulator approaches election. This is because the insurer is forward looking as well as prefectly aware of the regulator's actions in our model. Thus, the insurer is more likely to drop out around election time because he may know with certainty that he will not get the increase that he needs to remain profitable. In the real world, this is less likely and we find that there is no discernable pattern in drop outs across the election cycle. Note that the empirical dropout data is quite volatile, so while there appears to be a pattern in the dropout rates across the election cycle, it is statistically insignificant.

6.9 Counterfactual Experiments

Our empirical findings suggest that the LTCI market suffers from a variety of political frictions as well as high cost uncertainty. In this section, we consider what happens if some of these factors were removed. Starting from our estimated parameter values, we analyze how equilibrium supply and welfare would change if (1) short-term election cycle pressures were removed, (2) cost shocks were decreased, and (3) if political pressures were completely removed and regulators only maximized consumer welfare.

In the first experiment, we set the election cycle pressure parameter κ in equation 4 to 0 and estimate what would happen if regulators' had no term limits, or instead served in a rotating committee where appointment years are staggered. In order to preserve the same utility values from consumer surplus on average, we set γ to 48. The dotted red lines in Figures 8a and 8b show the equilibrium prices and application rates as a function of the election cycle respectively. We see that premium increases across the election cycle become flat, and average premiums are lower. Closely following price changes, application rates are also lowered and flattened. However, average dropout rates increase slightly in Figure 8c as price increases fall more than profits rise. In this calibration, much of the welfare gain from removing the regulatory friction is returned to consumers in the form of lower prices rather than to insurers.

In the second experiment, we change the mean of θ to 150, reflecting an approximately 50% reduction in average cost shocks. This represents a scenario in which actuarial technology improves, and insurers become better at predicting the cost of LTCI. The effect of this on prices and application rates are shown using the black dashed line in Figures 8a and 8b respectively. With a lower price shock, required rate increases and approved rate increases are both lower. As a result, application rates are lowered as well. However, there is still a downward sloping election cycle effect as regulators become tougher around election time. Finally, Figure 8cshows that dropout rates are much lower in this counterfactual, since companies do not experience as much profit loss over time.

In the last experiment, we remove all political frictions and only maximize consumer welfare in the regulator's objective function. In this scenario, the regulator would only grant rate increase requests if the likelihood and cost of insurer drop out was large enough to offset the cost shock to consumers. Looking at the dotted and dashed lines in Figures 8a and 8b, in equilibrium, we find that regulators become more stringent. Both the rate increases granted as well as rates of application become flatttened and lower over time. In Figure 8c, we also see that this leads to a higher dropout probability of firms. This suggests that in our model, the estimated cost of having some firms drop out is more than offset by the welfare gains consumers receive from lower premiums.

We conclude our counterfactual analysis by estimating welfare changes in each of the above experiments, which are summarized in Figure 9. Starting with the first experiment, which is shown in the first column labeled "No Election", we find that removing short-term cycles increases total social surplus (insurer plus consumer surplus) by $51,000 annually relative to the baseline scenario for each state and company. Thus, across all states and companies, this amounts to roughly $30.6 million annually, or $122.4 million across a four-year election cycle.[14],[15] While not a large amount, it demonstrates that even short-term election cycles frictions have a significant economic impact on this market.

One of the largest challenges facing the LTCI market is the size of its cost shocks due to the product's novelty as well as long life span. If there were technological or actuarial improvements that could help reduce the size of the uncertainty, that could strengthen the market considerably. Supporting this, looking at the second column of Figure 9 labeled "Low Cost," we find that reducing the magnitude of cost shocks by 50% increases consumer surplus by $49,000 and consumer surplus by $130,000 per state and company annually.

Finally, looking at the third column of Figure 9 labeled "CS Only," we show the estimated welfare change when regulators only seek to maximize consumer welfare. We see that this effectively transfers welfare from the insurers, who would each face a $160,000 loss per year, to consumers, who would gain $540,000 in surplus per year. In total, this amounts to an increase of in $380,000 total surplus per state and company, or $228 million nationwide. This is a rough estimate, because our model has abstracted away from market structure considerations such as dynamic price setting or collusion among companies. While price-setting in the LTCI market appears competitive today, it may change as the number of companies operating in the market dwindles. If so, then the interaction of market structure with regulatory action should be studied more closely in the future.

Overall, our counterfactual estimates complement our empirical findings and suggest that political frictions have nontrivial equilibrium effects on insurer profits and dropout. Even though the model does not predict strong dropout effects, political frictions and company dropout may still be correlated in the cross section if any of the model assumptions are too restrictive or if we are missing important state-space variables. For example, if more stringent regulators also face high election frictions or if states with high election frictions are also more mispriced, our welfare effects may be underestimated. Finally, our model naturally leads to some policy recommendations. For example, to resolve frictions arising from election cycles, consumers could elect a rotating committee of regulators or abolish the regulator term limits.

[14]After the data cleaning process outlined in Section 6.6.1 there were on average 12 companies operating in each state per year.

[15]Annual revenue estimates come from NAIC data and are derived from the 2014 estimates given in Nordman (2016).

7 Conclusion

Novel financial products are difficult to price, and they present significant regulatory challenges. The long-term care insurance (LTCI) market is relatively new, and it contains high cost uncertainty due to the long-run nature of the product. Its pricing difficulties have led to repeated negotiations between insurance companies and regulators, which in turn have impacted the ability of insurers to make profits. Examining these interactions over the last two decades, we find novel evidence that political frictions may have lead to persistent underpricing in the private LTCI market.

Our findings are important, because if LTCI is underpriced over an extended period, profit shortfalls will widen and companies may choose to drop out of the market. First, we show that regulators' political incentives can significantly predict their probability of approving a premium changes as well as the size of the premium change approved. For example, we show that regulators are tougher on premium increases when they have lower political capital or when they are closer to election year. Next, we find that tougher state regulators are correlated with lower insurer profits as well as higher rates of insurer dropout. Finally, a dynamic structural model allows us to calibrate equilibrium outcomes. In counterfactual simulations, we find that both removing election cycles as well as insurer profit considerations from the regulator's objective function can significantly improve social welfare by $228 million per year.

Not only do these findings have social implications for the millions of Americans entering old age who have to find funding for LTC, but there are valuable lessons from the LTCI market which could be extended to other settings. For instance, our model suggests that a nationally organized, rotating committee of regulators with staggered appointment dates can attenuate election cycle frictions and potentially improve novel financial markets. Some examples of these novel markets that exist today and are growing over time include subsidized plans under the Affordable Care Act (ACA) and hybrid annuity products seeking to replace LTCI.

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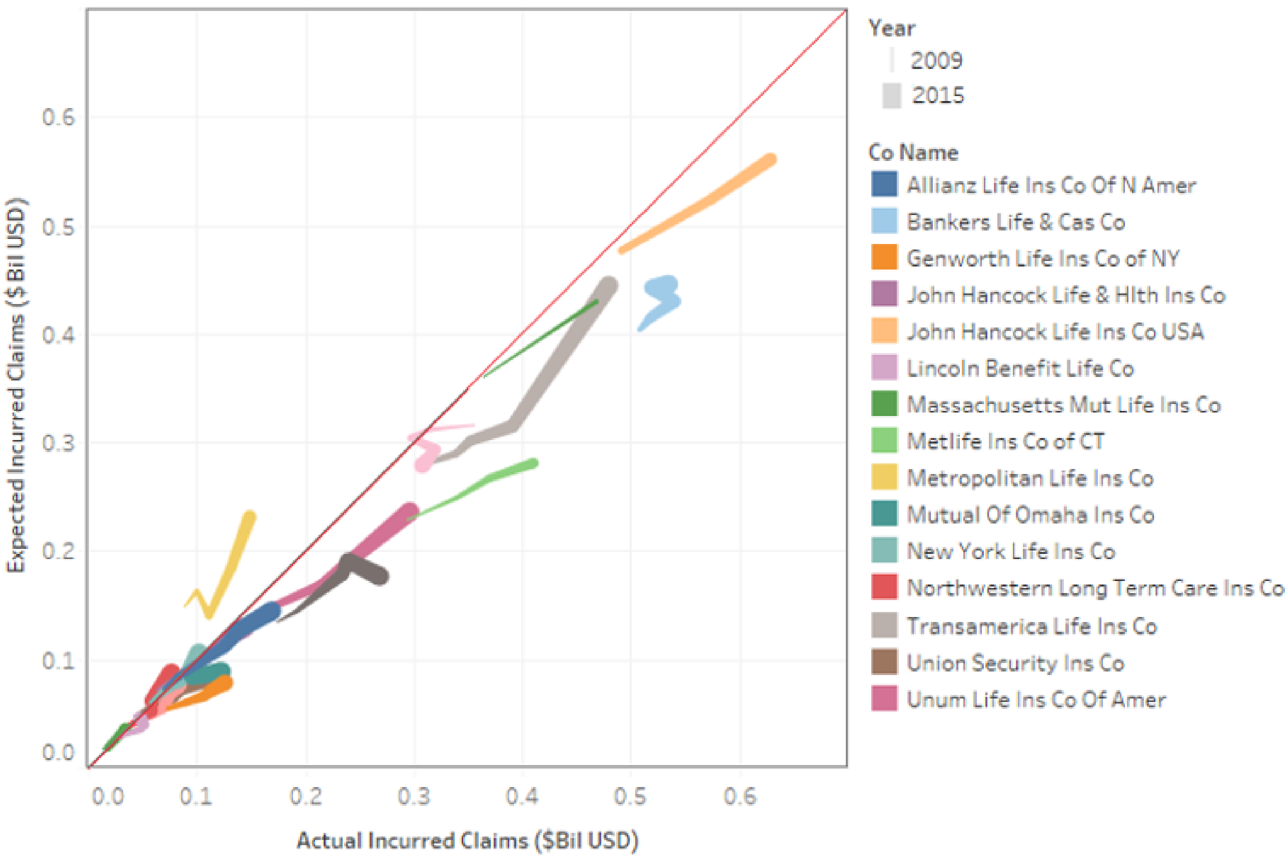
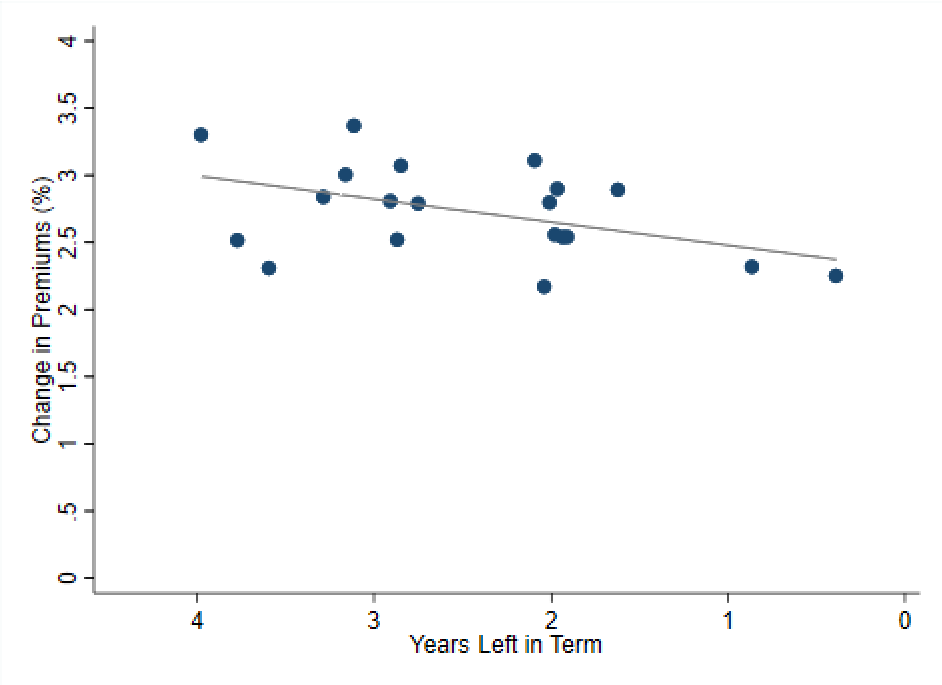
Figures

Figure 1: Actual To Expected LTCI Claims for Top 15 Companies



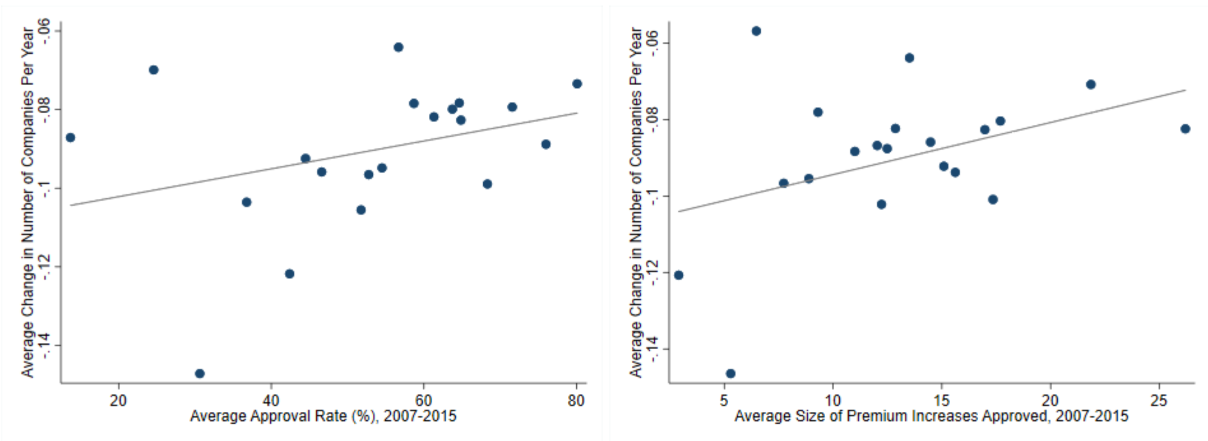
Source: Authors' calculations using NAIC Long-Term Care Experience Forms, 2009-2015

Figure 2: Annual Average Premium Increase Across the Election Cycle



Note: The scatterplot graphs average premium changes by regulator term length, controlling for state and year fixed effects. The data sample is drawn from the NAIC Long-Term Care Experience Forms, 2009-2015.

Figure 3: Effect of Regulator Stringency on Company Exit Per Year in State Market



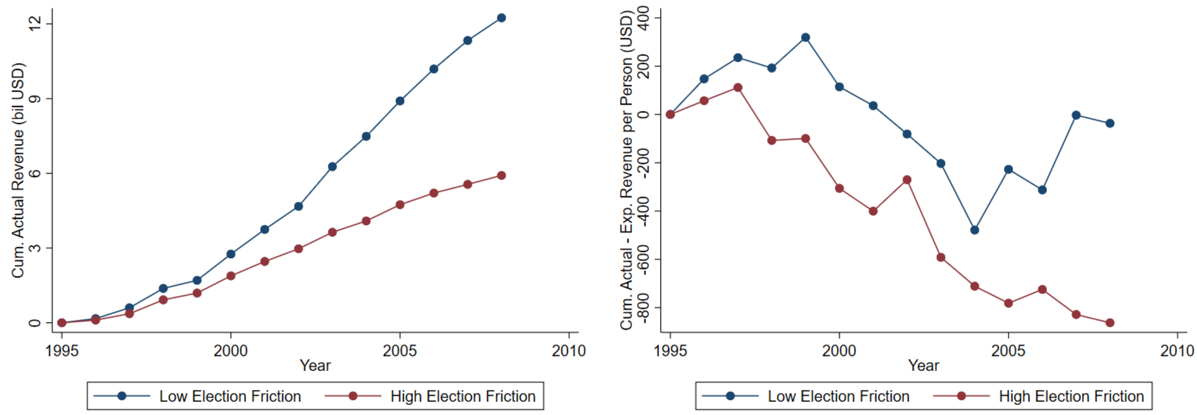
(a) Number of Company Exits versus Probability of Approval

(b) Number of Company Exits versus Size of Approved Increase

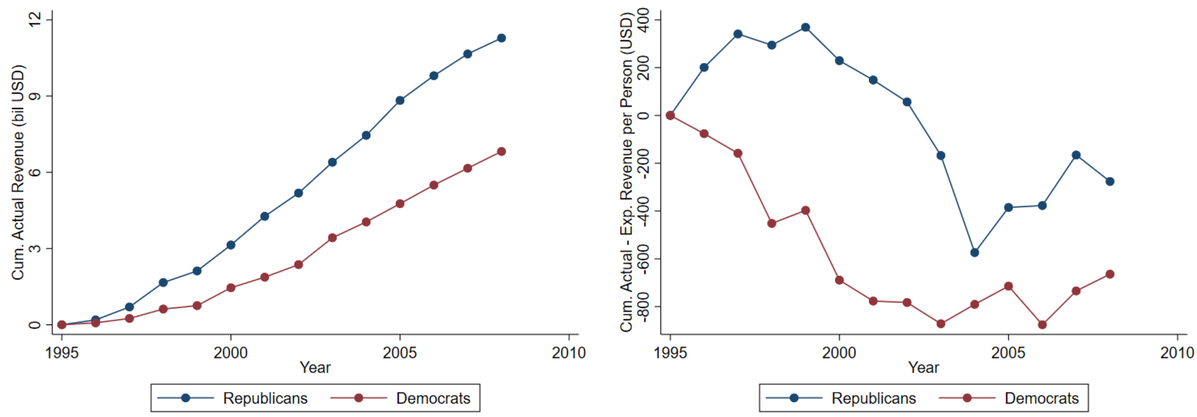
Source: Author's calculations using the California long-term care Rate and History Guide and NAIC LTC Experience Reports.

Figure 4: Political Frictions and Cumulative Profits, 1995-2008

(a) Panel A. Election Cycle Frictions

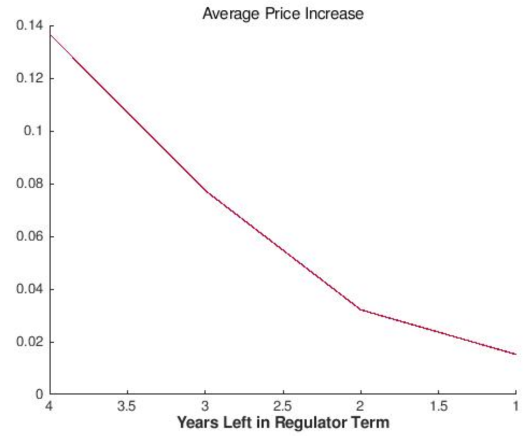


(b) Panel B. Political Affiliation and Stringency

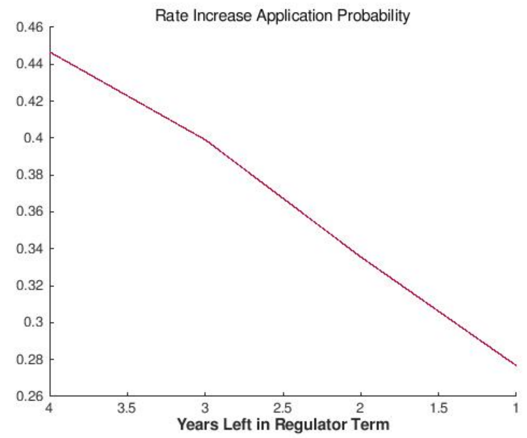


Source: Author's calculations using the California long-term care Rate and History Guide and NAIC LTC Experience Reports. High friction states, shown in red, are those where election cycles are estimated to have a larger effect on regulator behavior. Low friction states are shown in blue. States with Democratic regulators, which are generally more stringent on premium increase requests, are shown in red, and states with Republican regulators are shown in blue. See Section 5 for more details.

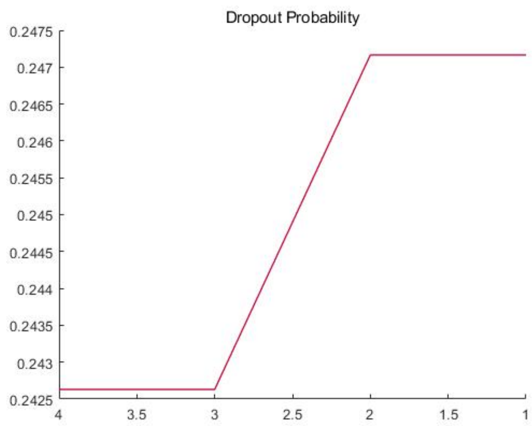
Figure 5: Optimal Policy Functions at the Estimated Parameters



(a) Average Predicted Price Increases Across the State Space



(b) Average Predicted Application Rates Across the State Space



(c) Average Predicted Dropout Rates Across the State Space

Figure 6: Optimal Policies of Insurer and Regulator

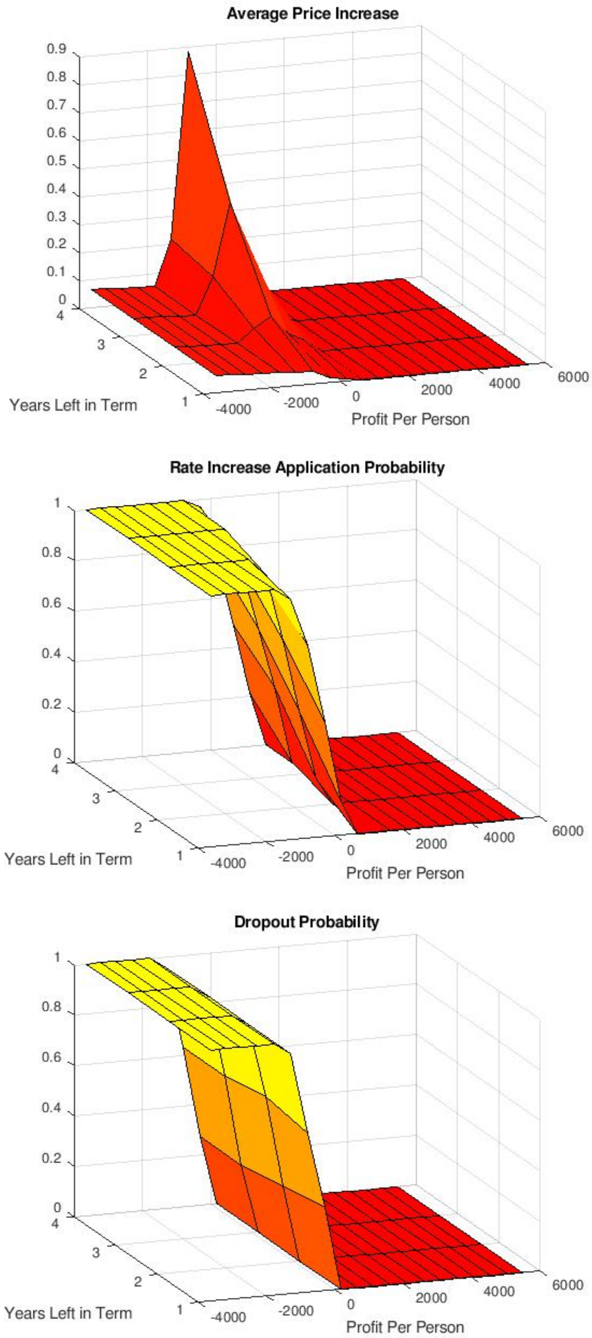
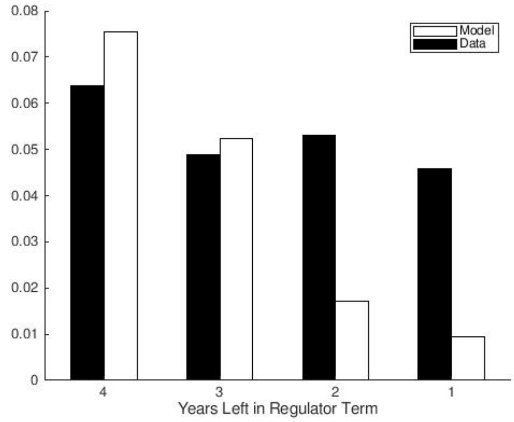
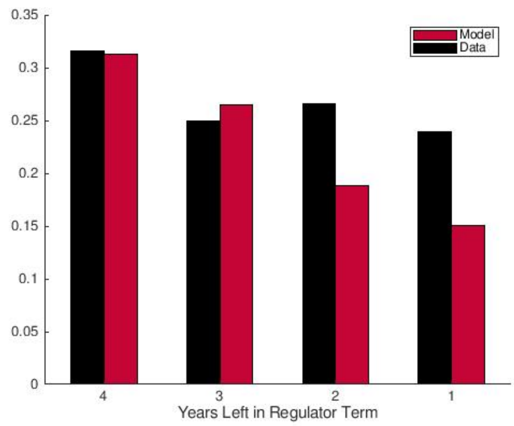


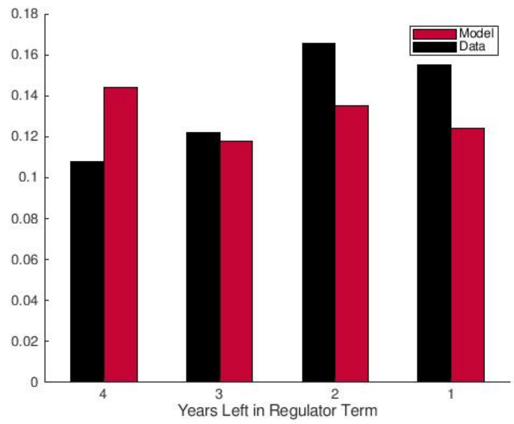
Figure 7: Model Fit for Conditional Moments



(a) Average Predicted And Actual Price Increases

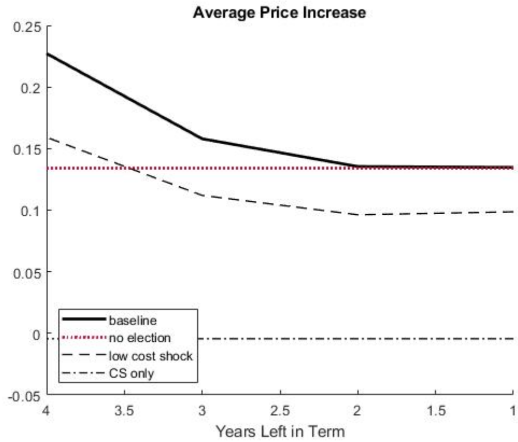


(b) Average Predicted And Actual Application Rates

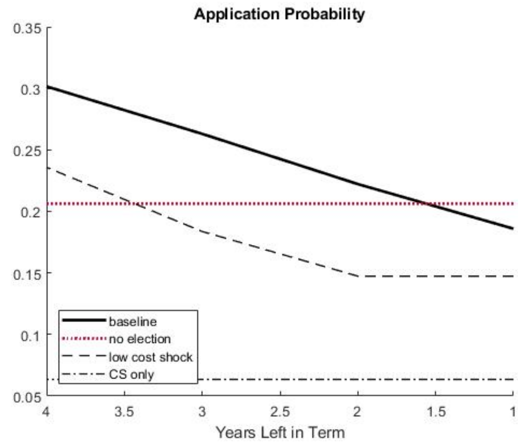


(c) Average Predicted And Actual Dropout Rates

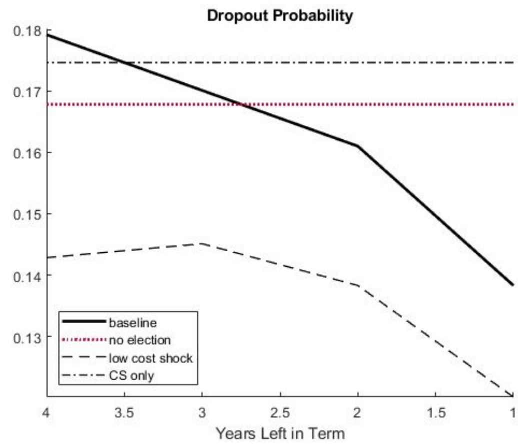
Figure 8: Counterfactual Policies



(a) Optimal Price Increases



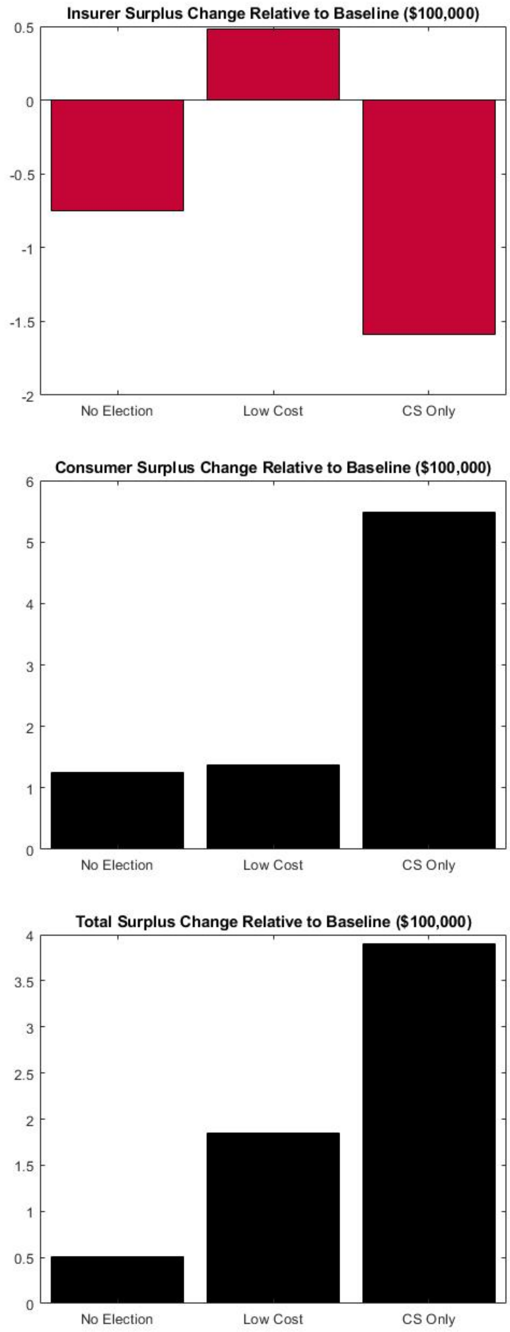
(b) Optimal Application Rates



(c) Optimal Dropout Rates

Note: The figure graphs optimal policies averaged across the state space for each scenario listed in the legend. All scenarios use baseline parameters unless otherwise stated. In the "No Election" scenario, we solve for optimal policies setting κ to 0 and γ to 48 in equation 4. In the "Low Cost" scenario, we set the average cost shock θ to be 150. Finally, in the "CS Only" scenario, we set the regulator's utility function such that he only maximizes consumer surplus.

Figure 9: Counterfactual Welfare Gains in the Short Term



Note: The figure graphs the relative welfare change averaged across all observations for the counterfactual scenarios depicted Figure 8. Flow utilities are dollarized using average marginal utility of income α. In the "No Election" scenario, we solve for optimal policies setting κ to 0 and γ to 48 in equation 4. In the "Low Cost" scenario, we set the average cost shock θ to be 150. Finally, in the "CS Only" scenario, we set the regulator's utility function such that he only maximizes consumer surplus.

Tables

Table 1: Effect of Election Year on Average Premium Increase

	Average Annual Premium Increase (%)	
	(1)	(2)
Years Left in Term	0.17**	0.17**
	(0.07)	(0.07)
Constant	2.06***	-1.67***
	(0.52)	(0.54)
Mean Dependent Variable	2.70	2.70
State FE and Year FE	Yes	Yes
Company FE	No	Yes
Number of Observations	51,437	51,437
R-squared	0.01	0.03

Note: The table displays the effects of regulator election cycle on average LTCI premium increases (measured in percentage points). Years left in term is equal to four when the regulator is just elected and equal to one in the year before election. If the regulator is appointed by the state governor, then the election cycle of the governor is used instead. Table A1 further breaks down the sample and estimates the above for elected and appointed regulators separately. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 2: Regulator Behavior Across the Election Cycle

	(1) Size of Increase (%)	(2) Number Approved	(3) Approval Rate (%), All	(4) Approval Rate (%), New
Years Left in Term	0.57**	0.06+	1.84**	2.09*
	(0.19)	(0.03)	(0.62)	(0.90)
Constant	12.98**	-1.37**	85.77**	85.74**
	(2.99)	(0.29)	(13.73)	(16.68)
Mean Dependent Variable	13.02	1.56	54.64	53.52
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	9,043	21,956	9,043	6,108
R-squared	0.17	0.19	0.21	0.20

Note: The table displays the effects of regulator election cycle on the magnitude and number of approved rate increases, the percentage of all open applications approved, and percentage of new applications approved, respectively. All observations at the company, state, year level and measured in percentage points. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 3: Company Behavior Across the Election Cycle

	(1) Size of Requested Increase (%)	(2) Number of Requests
Years Left in Term	0.03	0.04
	(0.11)	(0.03)
Constant	-6.01***	-0.93***
	(0.88)	(0.19)
Mean Dependent Variable	10.03	1.70
State FE and Year FE	Yes	Yes
Company FE	Yes	Yes
Number of Observations	21,956	21,956
R-squared	0.11	0.20

Note: The table displays the effects of regulator election cycle on the magnitude and number of rate requests, respectively. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 4: Effect of Winning Percentage on Rate Request Decisions

	Approval Probability (%)		Size of Increase (%)	
	(1)	(2)	(3)	(4)
Years Left in Term	2.40***	5.77	0.85***	6.11**
	(0.57)	(3.45)	(0.19)	(1.99)
Election Vote Percentage	0.01	0.17	-0.09***	0.16*
	(0.15)	(0.17)	(0.02)	(0.08)
Years Left in Term × Election Vote Percentage		-0.06		-0.09**
		(0.05)		(0.03)
Constant	48.07***	41.48**	1.57	-8.74
	(14.43)	(16.13)	(2.39)	(5.53)
Mean Dependent Variable	58.33	58.33	12.12	12.12
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	2,291	2,291	2,291	2,291
R-squared	0.24	0.24	0.16	0.17

Note: The table displays the effects of political capital on the the percentage of all open applications approved and magnitude of approved rate increases, respectively. Election Vote Percentage is a continuous variable representing the share of votes the current regulator received in the last election. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 5: Effect of Winning Margin on Rate Request Decisions

	Approval Probability (%)		Size of Increase (%)	
	(1)	(2)	(3)	(4)
Years Left in Term	2.39***	3.11**	0.84***	1.89***
	(0.57)	(1.00)	(0.19)	(0.57)
Winning Vote Margin	0.04	0.13	-0.04**	0.09**
	(0.07)	(0.09)	(0.01)	(0.04)
Years Left in Term × Winning Vote Margin		-0.03		-0.05**
		(0.03)		(0.02)
Constant	46.95***	47.88***	-2.64	-1.30
	(10.52)	(10.50)	(2.16)	(2.68)
Mean Dependent Variable	58.33	58.33	12.12	12.12
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	2,291	2,291	2,291	2,291
R-squared	0.24	0.24	0.16	0.17

Note: The table displays the effects of political capital on the the percentage of all open applications approved and magnitude of approved rate increases, respectively. Winning Vote Margin is a continuous variable representing the difference in share of votes the current regulator received over the closest runner-up in the last election. The higher the margin, the more votes the current regulator received. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 6: Effect of Political Party on Rate Request Decisions

	Approval Probability (%)		Size of Increase (%)	
	(1)	(2)	(3)	(4)
Years Left in Term	1.77***	1.40*	0.54***	0.50*
	(0.61)	(0.83)	(0.18)	(0.26)
Democrat	-8.30***	-10.27***	-3.91***	-4.14***
	(2.32)	(3.49)	(0.85)	(1.27)
Years Left in Term x Democrat		0.79		0.09
		(1.31)		(0.43)
Constant	87.35***	88.11***	13.72***	13.81***
	(14.03)	(13.99)	(3.15)	(3.21)
Mean Dependent Variable	51.78	51.78	12.54	12.54
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	9,043	9,043	9,043	9,043
R-squared	0.21	0.21	0.17	0.17

Note: The table displays the effects of political party on the the percentage of all open applications approved and magnitude of approved rate increases, respectively. Democrat is a dummy variable equalling 1 if the current insurance commissioner (or governor) identifies with the Democratic Party, and is 0 otherwise. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 7: Effect of Campaign Contributions on Rate Request Decisions

	Approval Probability (%)	Size of Increase (%)	Approval Probability (%)	Size of Increase (%)
	(1)	(2)	(3)	(4)
Years Left in Term	1.97*	0.66*	1.86*	0.75**
	(0.92)	(0.24)	(0.84)	(0.24)
Cash on Hand	-0.32*	-0.17**		
	(0.15)	(0.06)		
Campaign Contributions			0.20***	0.03***
			(0.04)	(0.01)
Constant	55.63***	-1.50	40.41***	-4.99**
	(13.44)	(2.20)	(10.85)	(2.02)
Mean Dependent Variable	57.54	11.88	57.43	11.85
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	2,167	2,167	2,148	2,148
R-squared	0.25	0.17	0.26	0.17

Note: The table displays the effects of campaign financing on the the percentage of all open applications approved and magnitude of approved rate increases, respectively. Cash on Hand is a continuous variable representing the net balance of current regulator's campaign at the beginning of the year. Campaign Contributions indicates how much money the regulator received during the year. Outcome variables are measured in hundreds of thousands. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 8: Differential Regulator Behavior Regarding the Same Application

	(1) Size of Increase (%)	(2) Approval Probability (%)	(3) Days Until Approval
Years Left in Term	0.076	1.28**	-1.84
	(0.23)	(0.47)	(1.97)
Constant	24.6***	94.4***	83.3***
	(1.44)	(1.96)	(11.6)
Mean Dependent Variable	21.44	88.22	155.91
Request FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Number of Observations	8,022	8,022	7,210
R-squared	0.67	0.64	0.62

Note: The table displays the effects of regulator election cycle on regulator behavior, controlling for application fixed effects. Standard errors, in parentheses, are clustered by application. Units of columns (1) and (2) in percentage points. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 9: Regression of Dropout on State Characteristics

	Nationwide Dropout Probability (%)			
	(1)	(2)	(3)	(4)
Election Pressure (state-weighted)	0.57**			0.30
	(0.17)			(0.20)
Applications Received (state-weighted)		0.002**		0.002*
		(0.001)		(0.001)
Rate Applications Approved (state-weighted)		-0.002**		-0.002*
		(0.001)		(0.001)
Annual Earned Premiums (Mil)			-0.09*	-0.07*
			(0.04)	(0.03)
Annual Claims Paid (Mil)			0.12	0.10
			(0.08)	(0.08)
Constant	0.28+	-0.63*	0.97**	-0.26
	(0.17)	(0.32)	(0.11)	(0.35)
Number of Observations	218	218	218	218
Pseudo R-squared	0.06	0.11	0.11	0.18

Note: The table displays the effects of various company-level characteristics on company dropout. Observations are at the company level. The outcome variable is a dummy variable indicating 1 if the company is not currently selling LTCI. Election pressure is the magnitude of the election cycle effect in each state. The first three LHS variables are state-weighted, meaning that election pressure, number of applications received by each state, and the number of applications approved in each states, are averaged across all the states each company operates in, weighted by the percentage of its premiums earned in that state. Outcome variables are measured in percentage points. Standard errors are in parentheses. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table 10: Insurer and Regulator Preference Parameter Estimates

Parameter	Notation	Estimate	S.E.
Rate Increase Application Cost	AppCost	105.35	15.45
LTC Business Scrap Value (millions)	ScrapValue	4.73	0.81
Overall Political Pressure	γ	106.20	18.74
Political Pressure Changes Over Election Cycle	κ	1.28	0.19

Notes: The table reports estimates for the preference parameters listed in the insurer and regulator utility functions from equations 3 and 4. Standard errors are computed using 25 bootstrap samples.

Table 11: Model Fit

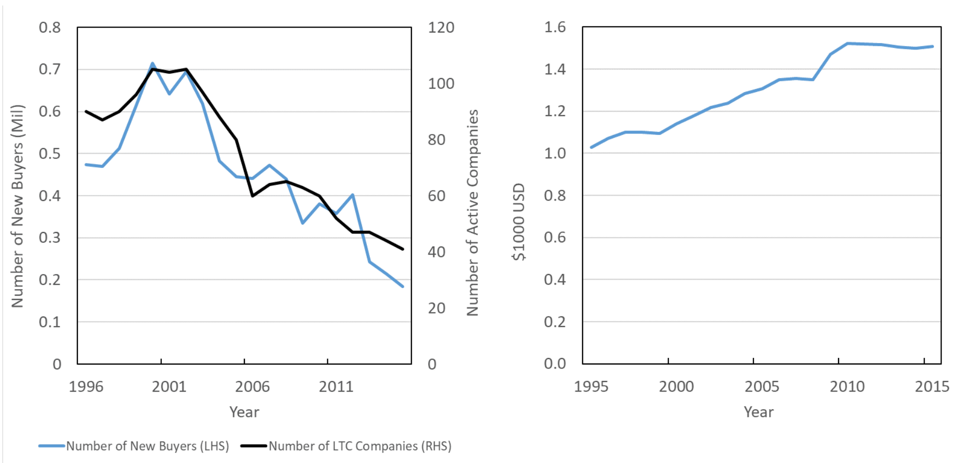
	Model Moments	Data Moments
Targeted Moments		
Mean Predicted Premium Increase	0.04	0.05
Mean Dropout Probability	0.13	0.14
Mean Application Probability	0.22	0.27
Un-Targeted Moments		
Std. Dev. Premium Increase	0.14	0.11
Std. Dev. Dropout Probability	0.34	0.35
Std. Dev. Application Probability	0.42	0.44

Appendices

Figure A1: Summary of LTCI Market Trends

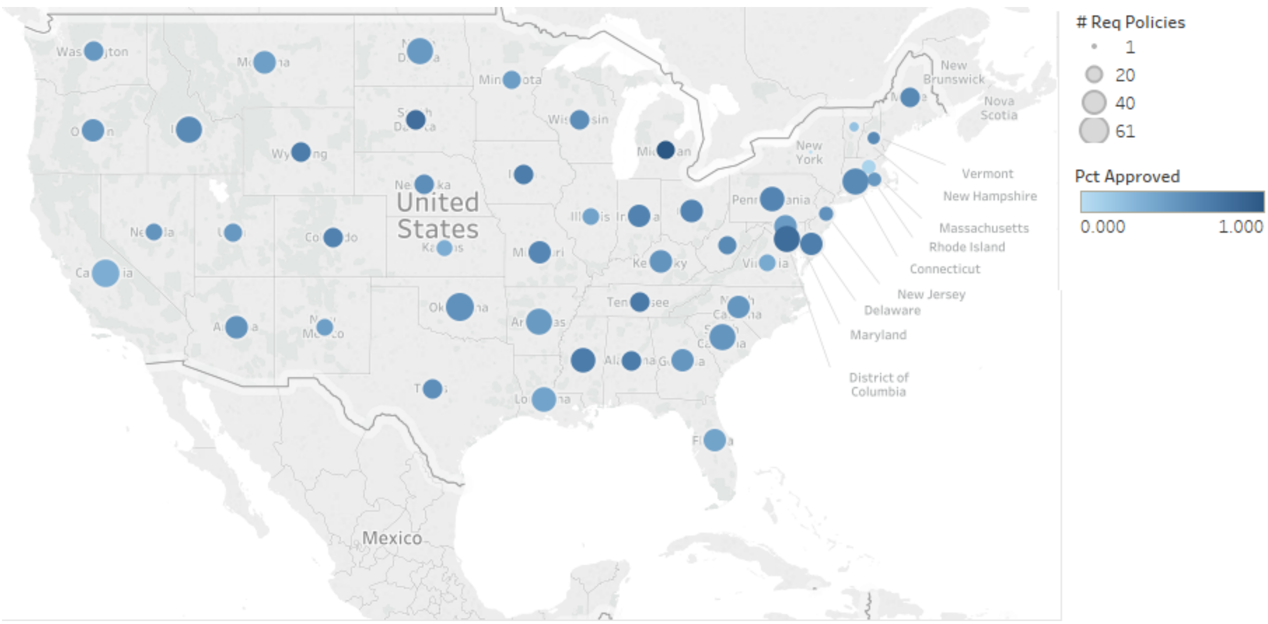
(a) New Buyers and Active Companies

(b) Average Annual LTC Premiums



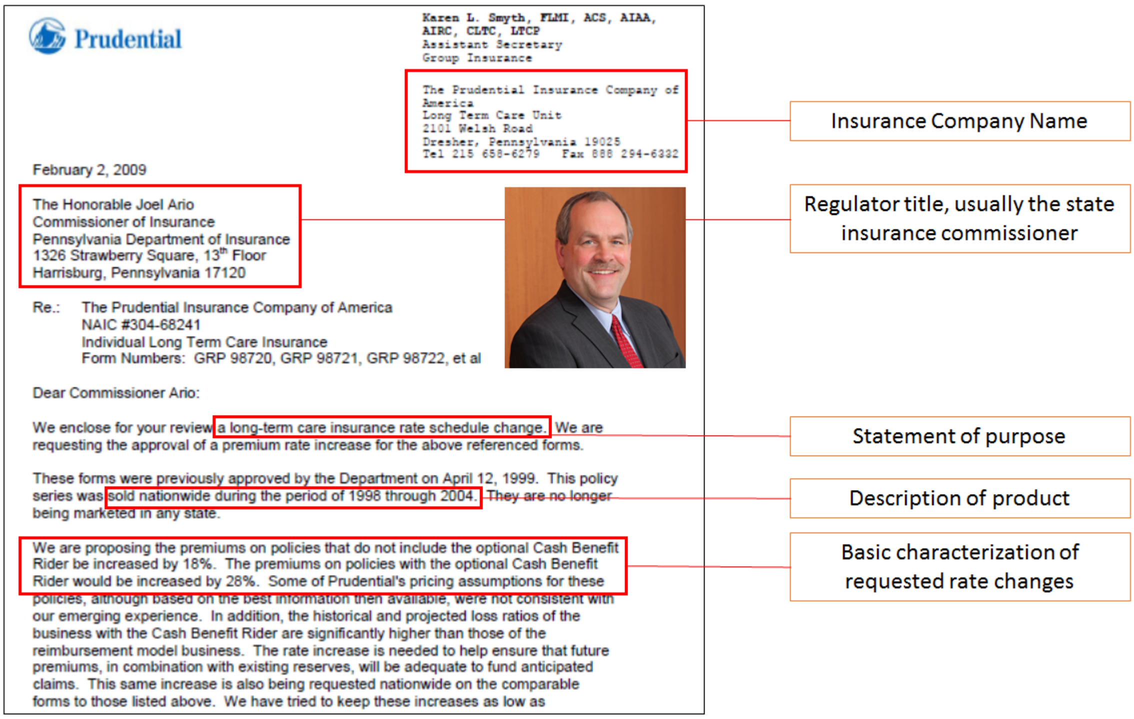
Source: Author's calculations using NAIC LTC Experience Forms.

Figure A2: Results of Genworth's Price Increase Requests Across States



Source: Authors' calculations using California's Rate History Data, 2007-2017

Figure A3: Sample PDF Submission to SERFF



Prudential

Karen L. Smyth, FLMI, ACS, AIAA,
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Assistant Secretary
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The Prudential Insurance Company of America
Long Term Care Unit
2101 Welsh Road
Dresher, Pennsylvania 19025
Tel 215 658-6279 Fax 888 294-6332

February 2, 2009

The Honorable Joel Ario
Commissioner of Insurance
Pennsylvania Department of Insurance
1326 Strawberry Square, 13th Floor
Harrisburg, Pennsylvania 17120

Re.: The Prudential Insurance Company of America
NAIC #304-68241
Individual Long Term Care Insurance
Form Numbers: GRP 98720, GRP 98721, GRP 98722, et al

Dear Commissioner Ario:

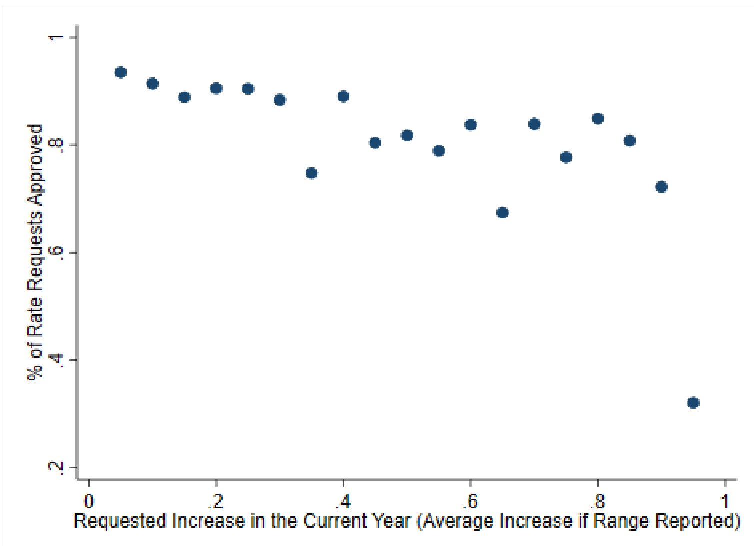
We enclose for your review a long-term care insurance rate schedule change. We are requesting the approval of a premium rate increase for the above referenced forms.

These forms were previously approved by the Department on April 12, 1999. This policy series was sold nationwide during the period of 1998 through 2004. They are no longer being marketed in any state.

We are proposing the premiums on policies that do not include the optional Cash Benefit Rider be increased by 18%. The premiums on policies with the optional Cash Benefit Rider would be increased by 28%. Some of Prudential's pricing assumptions for these policies, although based on the best information then available, were not consistent with our emerging experience. In addition, the historical and projected loss ratios of the business with the Cash Benefit Rider are significantly higher than those of the reimbursement model business. The rate increase is needed to help ensure that future premiums, in combination with existing reserves, will be adequate to fund anticipated claims. This same increase is also being requested nationwide on the comparable forms to those listed above. We have tried to keep these increases as low as

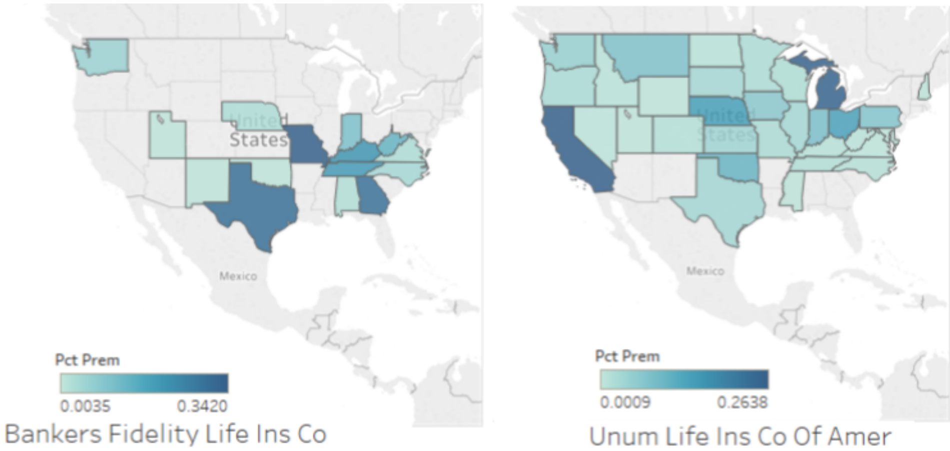
Source: Submission of rate request to the state of Pennsylvania in 2009 from Prudential Insurance Company, collected from the System for Electronic Rates & Forms Filing Database.

Figure A4: Trade-off Between Rate Increase Requested and Probability of Approval



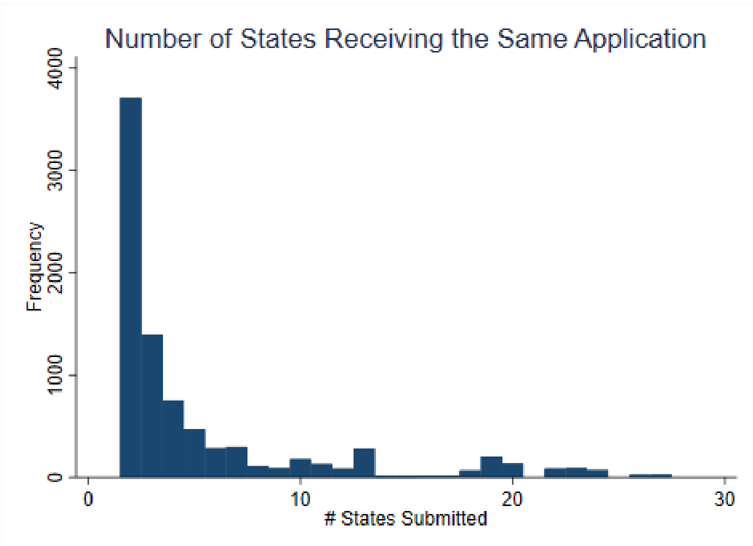
Source: Authors' calculations using the California long-term care Rate and History Guide.

Figure A5: Geographic Concentrations of Bankers Fidelity and Unum



Source: Author's calculations using the NAIC LTC Experience Reports.

Figure A6: Distribution of Multi-State Requests



Source: Authors' calculations using the California long-term care Rate and History Guide. Requests submitted to multiple states were determined to be the same request if the two (or more) submissions fulfilled the criteria listed in the text.

Table A1: Effect of Election Cycles on Elected versus Appointed Regulators

	Commissioner Directly Elected		Appointed Commissioner	
	(1)	(2)	(3)	(4)
	Approval Probability	Size of Approved Increase	Approval Probability	Size of Approved Increase
Years Left in Term	1.86**	0.68**	1.51	0.38
	(0.74)	(0.24)	(0.99)	(0.26)
Constant	51.27***	-3.70	84.59***	13.71***
	(10.78)	(2.21)	(16.21)	(3.54)
Mean Dependent Variable	58.03	11.95	52.52	13.15
State FE and Year FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Number of Observations	2,369	2,369	6,674	6,674
R-squared	0.23	0.16	0.21	0.17

Note: The table above shows shows how the regulators' election cycle affects his probability of approving a rate increase request (columns 1 and 3) as well as the size of increase approved (columns 2 and 4). In addition, we test how the type of regulator, either elected or appointed, affects this decision. The analyses in columns 1 and 2 only contain states with directly elected insurance commissioners, while the analyses in columns 3 and 4 only contain states with insurance commissioners that are appointed by the governor. Standard errors, in parentheses, are clustered by state. Levels of significance: + 10%, * 5%, ** 1%, *** 0.01%.

Table A2: Elected and Appointed Commissioners

State	Elected	Governor-Appointed	Neither
Alabama		X	
Alaska			X
Arizona		X	
Arkansas		X	
California	X		
Colorado		X	
Connecticut		X	
Delaware	X		
Florida	X*		
Georgia	X		
Hawaii		X	
Idaho		X	
Illinois		X	
Indiana		X	
Iowa		X	
Kansas	X		
Kentucky		X	
Louisiana	X		
Maine		X	
Maryland		X	
Massachusetts		X	
Michigan		X	
Minnesota		X	
Mississippi	X		
Missouri		X	
Montana	X		
Nebraska		X	
Nevada		X	
New Hampshire		X	
New Jersey		X	
New Mexico			X
New York		X	
North Carolina	X		
North Dakota	X		
Ohio		X	
Oklahoma	X		
Oregon			X
Pennsylvania		X	
Rhode Island			X
South Carolina		X	
South Dakota		X	
Tennessee		X	
Texas		X	
Utah		X	
Vermont		X	
Virginia			X
Washington	X		
West Virginia		X	
Wisconsin		X	
Wyoming		X	

Note: Florida's insurance commissioner became an appointed position in 2003.

Table A3: Summary Statistics

Variable	Obs	Mean	Standard Deviation
Annual Premium Change (%)	55,661	2.70	21.13
Annual Total Claims (Mil)	59,072	3.35	18.41
Annual Total Premiums (Mil)	59,072	7.55	36.72
Lives in Force	38,769	1278	5434
Cumulative Company Dropout (state-level)	13,120	0.30	0.46
Commissioner Directly Elected	59,072	0.23	0.42
Election Vote Percentage (%)	16,145	57.55	9.39
Election Year	50,972	0.24	0.42
Average Size of Approved Increases (%)	10,233	12.35	16.35
Average Size of Requested Increases (%)	23,419	10.20	22.38
Number of Policies Approved	23,419	1.66	5.14
Number of Increases Requested	23,419	1.92	5.50
Probability of Approval, All Open Filings (%)	10,228	50.09	47.60
Probability of Approval, New Filings (%)	6,563	50.91	48.68
Applied for Rate Increase	23,419	0.24	0.43
Campaign Contributions (Mil)	4,292	0.52	2.75
Unique Companies			235

Note:statetab All observations at the state, company, and year level. Election Year, Company Dropout, Commissioner Directly Elected are binary variables indicating that the current observation is in an election year, that the current observation is the year time the company submitted advertising material for approval, and that the insurance commissioner is directly elected rather than appointed by the governor. Election Vote Percentage is the share of votes the commissioner received in the latest election.

Table A4: Estimation Sample Summary Statistics

Variable	Mean	Standard Deviation
Annual Total Claims (Mil)	4.44	9.79
Annual Total Premiums (Mil)	7.06	14.50
Lives in Force	4163.98	8491.40
Company Dropout	0.14	0.35
Election Year	0.26	0.44
Annual Approved Increase (%)	5.30	10.68
Annual Requested Increase (%)	7.93	16.33
Number of Policies Approved	2.55	7.96
Number of Increases Requested	3.38	9.00
Applied for Any Rate Increase	0.27	0.44
Market Share	0.0040	0.0081
Total Observations		2,803
Unique Companies		59

Note: All observations at the state, company, and year. Election Year, Company Dropout, Applied for Rate Increase are binary variables indicating that the current observation is in an election year, that the current observation is the last for the company in that state, and that an application for a rate increase was submitted, respectively. Market share is defined as the number of covered lives for a particular company, state, and year divided by the total number of 50+ year olds without Medicaid coverage in that state and year.